Cyclicality in Catastrophic and Operational Risk Measurements

ABSTRACT

Using equity returns for financial institutions we estimate both catastrophic and operational risk measures over the period 1973-2001. We find evidence of cyclical components in both the catastrophic and operational risk measures obtained from the Generalized Pareto Distribution and the Skewed Generalized Error Distribution. Our new, comprehensive approach to measuring operational risk shows that approximately two thirds of financial institutions' returns represents compensation for operational risk.

Keywords: operational risk, catastrophic risk, value at risk, extreme value theory, skewed fat tailed distribution.

Cyclicality in Catastrophic and Operational Risk Measurements

A natural point of departure for all elements of business risk measurement is the past. Future trends and current metrics are often extrapolated from an historical data series. However, this process is fundamentally flawed if there are cyclical factors that impact business measures of risk or performance. Historical data on operational risk gathered during an economic expansion may not be relevant for a period of recession. Estimates of default risk and recovery rates incorporate cyclical components that are correlated to systematic risk factors, such as macroeconomic fluctuations and regulatory shifts. All too frequently, however, researchers and practitioners alike ignore these cyclical factors and blithely extend an unadjusted trend line into the future. The metrics obtained using this methodology are fundamentally flawed. By aggregating across different macroeconomic regimes, these historical estimates do not accurately reflect either time period. It is the goal of this paper to demonstrate the importance of developing models to adjust for systematic and cyclical risk factors in business metrics.

Neglect of cyclical components in business and risk measurement is not the result of an oversight. Indeed, currently one of the major impediments to the adoption of the BIS New Capital Accord for international bank regulations is the proposal's neglect of cyclical factors.[1] Concerns focus on the procyclical nature of credit risk. That is, if there are systemic cyclicalities in bank risk exposures, for example, then aggregate bank capital requirements that are based on risk measurements with significant cyclical components may experience cyclical swings that may have unintended, adverse impacts on the macroeconomy. For example, if credit risk models overstate (understate) default risk in bad (good) times, then internal bank capital requirements will be set too high (low) in bad (good) times, thereby forcing capital-constrained banks to retrench on lending during recessions and expand lending during booms.[2] Since most banks are subject to the same cyclical fluctuations, the overall macroeconomic effect of capital regulations is to exacerbate business cycles, thereby worsening recessions and overheating expanding economies – that is, the risk-adjusted capital requirements proposed by the BIS Basel Committee on Banking Supervision are procyclical.[3]

Academic and business researchers acknowledge the importance of cyclical factors in business measures of risk and performance. In a series of articles, Allen and Saunders (2002a, 2002b) survey the

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[1] For description of the BIS proposals, see BIS (January 2001, March 2001, September 2001), BIS (March 2002).

[2] Hillegeist et al. (2002) compare accounting-based credit risk measurement models (Altman's Z-score and Ohlson's O-score) to the market-based option pricing model of default risk and find that the addition of market factors (in this case, equity prices) significantly improves explanatory power, thereby indicating the presence of a systematic market risk factor in default probabilities. Bongini et al. (2002) obtain similar results when comparing accounting data, stock prices and credit ratings as indicators of bank fragility.

[3] Of course, prudential supervision could be used to mitigate these systemic factors, as in the case of "ring-fencing," which is the supervisory process of "protecting a bank from adverse impact of events occurring in the wider corporate group, especially those engaging in unsupervised activities." BIS, March (2002, p. 51).

state of the art in adjusting risk measures for macroeconomic factors. Lowe (2002) suggests that a business cycle view would result in recessions following expansions and vice versa in a pattern similar to a sine wave. However, the poor track record of economic forecasting might cast doubts on such a simple specification of cyclical effects. Lowe (2002) acknowledges the difficulties in incorporating more complex cyclical models. Most risk measurement models, therefore, assume that key parameters are independent of macroeconomic factors. This paper tests and rejects that hypothesis. We explicitly test whether cyclical risk factors are incorporated into measures of operational risk and catastrophic risk exposures in financial institutions. We find that cyclical factors are significant components of both catastrophic and operational risk. Thus, neglect of cyclicality undermines accuracy in risk measurement.

Catastrophic risk is estimated using two different methodologies: Extreme Value Theory implemented using the Generalized Pareto Distribution (GPD) of Pickands (1975), and a Skewed Fat-Tailed Distribution implemented using the Skewed Generalized Error Density (SGED) of Bali and Theodossiou (2003). The database is presented and the GPD estimation is described in Section 1, whereas the SGED estimation results are contained in Section 2. The cyclical factors are defined and their significance is tested in Section 3. We limit our attention to catastrophic risk in Sections 1-3. In Section 4, we define a new, residual measure of operational risk that is quite comprehensive. We utilize both the GPD and SGED models to estimate the operational risk measurements. Evidence of cyclicality in these operational risk measurements is examined in Section 5. Finally, Section 6 concludes and makes recommendations for future research.

1. Estimating Catastrophic Risk Using the Generalized Pareto Distribution

Catastrophic risk events result in extremely low equity returns, as compared to a monthly cross section of equity returns. Catastrophic risk may be generated by extreme shifts in interest rates, exchange rates, equity prices, commodity prices, credit quality or operational performance. Thus, catastrophic risk contains elements of market risk, credit risk and operational risk. In this section, we focus on catastrophic risk, whatever its source. Subsequently, in Section 4, we decompose catastrophic risk into its market risk, credit risk and operational risk components and analyze the cyclical effects in the operational risk (residual) component.

1.1 The Database

We analyze catastrophic risk using a sample comprised of financial intermediaries. We limit our study of catastrophic risk to financial institutions in order to define a relatively homogenous group of firms that have broad risk exposures. Financial intermediaries maintain risk inventories as a normal course of conducting business – making markets, underwriting securities and holding portfolios comprised of financial securities. Thus, we believe that a sample of financial institutions offers the best opportunity to observe a wide range of risk exposures, thereby making it possible to decompose catastrophic risk into its component parts.

Although financial intermediaries have similar characteristics, they are not completely homogenous. For example, banks differ somewhat from insurance companies and from broker/dealers.[4] We construct our sample by searching CRSP for all firms traded on either the NYSE, AMEX or Nasdaq that had primary SIC codes of 6XXX over the time period ranging from January 1973 to December 2001. We obtain monthly data (including dividends) from CRSP, resulting in a total of 513,194 observations of monthly equity returns.[5] We define the catastrophic risk tail of the monthly return distribution to be those returns in the lowest 10% of each of the monthly cross sections of observations. In this section, we perform our analysis on those lower tail observations only, thereby limiting our analysis to 51,319 observations. In Section 2, we estimate the entire distribution for financial institutions' monthly equity returns.

The effect of diversification in risk reduction is quite apparent in comparisons of the distribution of SIC codes in the lower tail of the return distribution to the entire distribution comprised of all monthly equity returns on financial institutions. Holding companies (SIC code 67, which includes bank holding companies and mutual funds) represent 48% of the entire sample, but only 39% of the observations in the lower return tail of equity returns. Moreover, depository institutions (SIC code 60) have relatively less downside risk exposure than other financial institutions (comprising 20% of the lower tail observations, but 25% of the entire database), perhaps as a result of constraining banking regulations, such as minimum capital requirements, as well as access to the governmental safety net in the form of deposit insurance and lender of last resort privileges. In contrast, nondepository credit institutions (SIC code 61) were more heavily represented in the lower tail of equity returns (comprising 9% of the observations) than in the entire sample (comprising 5% of the observations). This may reflect the periodic upheavals in the mortgage banking business in the U.S. Other classifications that experienced relatively greater amounts of downside risk over the sample period were real estate firms (SIC code 65, comprising 9% of the tail observations, but only 5% of the entire sample), security and commodity brokers (SIC code 62, comprising 6% of the tail observations, but only 3% of the entire sample) and insurance companies (SIC code 63, comprising 14% of the tail observations, but only 12% of the entire sample).

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[4] These lines of distinction have become somewhat blurred by the passage of the Gramm-Leach-Bliley Act of 1999 which permits consolidation of banking, insurance and securities activities into a single financial holding company. In Section 3, we distinguish different types of financial intermediaries by their regulatory and market structure environments.

[5] To check for the possibility of window dressing of quarter-end and year-end data, as found in Allen and Saunders (1992), we constructed our own monthly returns using mid-month to mid-month equity prices. Our results were quite similar to those obtained using CRSP monthly returns; therefore, we do not report them here.

1.2 GPD Methodology

Extremes are generally defined as excesses over a high or low threshold, and can be modeled by the generalized Pareto distribution (GPD) of Pickands (1975). This paper concentrates on the lower (left) tail of the return distribution, and obtains the extremes from the cross-section of stock returns for each month from January 1973 to December 2001.[6] More specifically, extreme returns are measured by the 10% left tail of the empirical distribution of stock returns r.

Let us call $f(r)$ the probability density function (pdf) and $F(r)$ the cumulative distribution function (cdf) of r, which can take values between l and u.[7] First, we choose a low threshold l so that all $r_i < l < 0$ are defined to be in the negative tail of the distribution, where $r_1, r_2, \ldots, r_n$ are a sequence of stock returns. Then we denote the number of exceedances of l (or stock returns lower than l) by

$$N_u = \text{card}\{i: i = 1, \ldots, n, r_i > n\}, \tag{1}$$

and the corresponding excesses by $M_1, M_2, \ldots, M_{N_u}$. The excess distribution function of r is given by:

$$F_l(y) = P(r - l \geq y \mid r < l) = P(M \geq y \mid r < l), \quad y \leq 0 \tag{2}$$

Using the threshold l, we now define the probabilities associated with r:

$$P(r \leq l) = F(l) \tag{3}$$

$$P(r \leq l + y) = F(l + y) \tag{4}$$

where $y < 0$ is an exceedence of the threshold l. Finally, let $F_l(y)$ be given by

$$F_l(y) = \frac{F(l) - F(l + y)}{F(l)} \tag{5}$$

We thus obtain the $F_l(y)$, the conditional distribution of *how* extreme a r_i is, given that it already qualifies as an extreme. Pickands (1975) shows that $F_l(y)$ will be very close to the generalized Pareto distribution $G_{\min,\xi}$ in equation (6) if l is a low threshold:

$$G_{\min,\xi}(M; \mu, \sigma) = \left[1 + \xi\left(\frac{\mu - M}{\sigma}\right)\right]^{-1/\xi} \tag{6}$$

where μ, σ, and ξ are the location, scale, and shape parameters of the GPD, respectively. The *shape* parameter ξ, called the tail index, reflects the fatness of the distribution (i.e., the weight of the tails),

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[6] Campbell et al. (2001), Goyal and Santa-Clara (2003), and Bali et al. (2003) measure average stock risk and average idiosyncratic risk in each month as the cross-sectional equal-weighted and value-weighted average of the variances of all the stocks traded in that month. Similarly, we use the cross-section of stock returns to estimate value at risk for each month from January 1973 to December 2001.

[7] For example, a random variable distributed as the normal gives $l = -\infty$ and $u = +\infty$.

whereas the parameters of *scale* σ and of *location* μ represent the dispersion and average of the extremes, respectively.[8]

Two parametric approaches are commonly used to estimate the extreme value distributions: (1) the maximum likelihood method which yields parameter estimators which are unbiased, asymptotically normal, and of minimum variance. (2) the regression method which provides a graphical method for determining the type of asymptotic distribution.[9] In this paper the maximum likelihood method is used to estimate catastrophic and operational risk parameters.

Suppose that the generalized extreme value distribution for the minima, $G_{min}(\Phi; x)$, has a density function $g_{min}(\Phi; x)$, where $\Phi = (\xi, \mu, \sigma) \in \Re \times \Re \times \Re_+$ consists of a *shape* parameter ξ, a *location* parameter μ and a *scale* parameter σ. Then the *likelihood function* based on the data for the minimum variable $M_T = (M_1, M_2,\ldots, M_T)$ is given by

$$L(\Phi; M_T) = \prod_{i=1}^{T} g_{\min}(\Phi; M_i) \tag{7}$$

Denote the *log-likelihood function* by $l(\Phi; M_T) = \ln L(\Phi;M_T)$. The maximum likelihood estimator (MLE) for Φ then equals

$$\hat{\Phi}_T = \arg\max_{\Phi\in\Theta} l(\Phi; M_i) \tag{8}$$

where $\hat{\Phi}_T = \hat{\Phi}_T(M_1, M_2,\ldots, M_T)$ maximizes $l(\Phi; M_T)$ over an appropriate parameter space Θ.

The generalized Pareto distribution presented in (6) has a density function for the minima,

$$g_{\min}(\Phi; x) = \left(\frac{1}{\sigma}\right)\left[1+\xi\left(\frac{\mu-M}{\sigma}\right)\right]^{-\left(\frac{1+\xi}{\xi}\right)} \tag{9}$$

which yields the log-likelihood function:

$$\mathrm{LogL}_{\mathrm{GPD}} = -n\ln\sigma - n\left(\frac{1+\xi}{\xi}\right)\sum_{i=1}^{n} \ln\left(1+\xi\left(\frac{\mu-M_i}{\sigma}\right)\right) \tag{10}$$

Differentiating the log-likelihood function in (10) with respect to μ, σ, and ξ yields the first-order conditions of the maximization problem. Clearly, no explicit solution exists to these nonlinear equations, and thus numerical procedures or search algorithms are required.

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[8] The generalized Pareto distribution presented in equation (6) nests the standard *Pareto* distribution, the *uniform* distribution, and the standard *exponential* distribution. The shape parameter, ξ, determines the tail behavior of the distributions. For $\xi > 0$, the distribution has a polynomially decreasing tail (Pareto). For $\xi = 0$, the tail decreases exponentially (exponential). For $\xi < 0$, the distribution is short tailed (uniform).

[9] Details and presentation of alternative statistical estimation methods can be found in Leadbetter, Lindgren, and Rootzen (1983), Resnick (1987), Embrechts, Kluppelberg, and Mikosch (1997), Longin (1996), and Bali (2003).

Figures 1A, 1B, and 1C, respectively, present the location, scale, and shape parameter estimates (denoted *μ-GPD, σ-GPD* and *ξ-GPD*, respectively) from January 1973 to December 2001. For example, Figure 1A graphs the monthly mean of the GPD. The lowest value of the location parameter of the catastrophic risk tail was –0.38 and was obtained in October 1987, the month of the market crash. The highest monthly mean was 0.02 for January 1976, the start of the recovery from the deep 1974-1975 recession. Tail variance (shown in Figure 1B) was minimized during February 1980 at 0.002504 (0.05004 for standard deviation). This coincides with the passage of the Depository Institutions Deregulation and Monetary Control Act (DIDMCA) which lifted interest rate ceilings, increased deposit insurance coverage to $100,000, allowed banks to offer savings accounts paying market interest rates, expanded lending powers for thrift institutions, and set uniform reserve requirements for state and nationally chartered banks. The DIDMCA was heralded as a revolutionary improvement in the regulatory environment governing financial intermediation. On the other hand, tail volatility was maximized for the December 1991 month with a variance of 0.16 (standard deviation of 0.40). This coincided with the implementation of Basel capital accords, the first risk-adjusted international bank capital requirements. Moreover, Figure 1C plots the monthly tail-thickness parameters which show that catastrophic risk is characterized by fat tails since the estimated shape parameters are positive in most cases.

2. Estimating Catastrophic Risk Using the Skewed Generalized Error Distribution

In Section 1, we focused on the lower tail of the return distribution. That is, we defined catastrophic risk based on the lowest 10% of all monthly equity returns for financial institutions during any month over the period ranging from January 1973 to December 2001. In this section, we investigate the shape of the entire return distribution. Thus, the results obtained in Section 2 place catastrophic risk into the context of the entire probability distribution of monthly equity returns for financial intermediaries. Moreover, in this section, we compare the Value at Risk (VaR) measures obtained using the two different methodologies of Sections 1 and 2.

In order to depict the range of all observed monthly equity returns, we must make some assumptions about the presumed shape of the equity return distribution. We start with the simplest and most restrictive assumption – normality. Then we proceed to a general distribution, the Skewed Generalized Error Distribution (SGED), thereby permitting the estimation of four distributional moments – mean, standard deviation, skewness and kurtosis. We submit these distributional assumptions to statistical tests (likelihood ratio test) of the null hypothesis (normality) against the SGED assumption. Monthly likelihood ratio tests strongly reject the normality assumption at the 1% significance level for almost all months from January 1973 to December 2001.[10]

2.1 The Properties of the Skewed Generalized Error Distribution (SGED)

Subbotin (1923) introduces the Generalized Error Distribution (GED) as special cases of Laplace, normal, and uniform distributions. The symmetric GED density is given by equation (11):

$$f_v(\varepsilon_t) = \frac{v \ \exp[(-1/2)\,|\,\varepsilon_t / \Pi\,|^v]}{\Pi \ 2^{[(v+1)/v]} \ \Gamma(1/v)} \tag{11}$$

where r_t is the return at time $t, \varepsilon_t = \dfrac{r_t - \mu}{\sigma}$ is the standardized return at time t, $\Gamma(a) = \int_0^{+\infty} x^{a-1} e^x dx$ is the gamma function, $\Pi = \left[\dfrac{2^{(-2/v)}\Gamma(1/v)}{\Gamma(3/v)}\right]^{1/2}$, and $v > 0$ is the degrees of freedom or tail-thickness parameter. For $v = 2$, the GED yields the normal distribution, while for $v = 1$ it yields the Laplace or the double exponential distribution. If $v < 2$, the density has thicker tails than the normal, whereas for $v > 2$ it has thinner tails.

The GED is used by Box and Tiao (1962) to model prior densities in Bayesian estimation, Nelson (1991) to model the distribution of stock market returns, and Hsieh (1989) to model the distribution of exchange rates. Bali and Theodossiou (2003) introduce an asymmetric (or skewed) version of the GED. The Skewed Generalized Error Distribution (SGED) adds an additional moment, skewness, to the GED formulation. The probability density function for the SGED is

$$f(r;\mu,\sigma,k,\lambda) = \frac{C}{\sigma}\exp\left(-\frac{1}{[1+sign(r-\mu+\delta\sigma)\lambda]^k \theta^k \sigma^k}\left|r-\mu+\delta\sigma\right|^k\right) \tag{12}$$

where,

$$C = \frac{k}{2\theta}\Gamma\left(\frac{1}{k}\right)^{-1} \tag{13}$$

$$\theta = \Gamma\left(\frac{1}{k}\right)^{-1/2}\Gamma\left(\frac{3}{k}\right)^{-1/2} S(\lambda)^{-1} \tag{14}$$

$$\delta = 2\lambda\, A\, S(\lambda)^{-1} \tag{15}$$

$$S(\lambda) = \sqrt{1 + 3\lambda^2 - 4A^2\lambda^2} \tag{16}$$

[10] The likelihood ratio test results are available upon request.

$$A = \Gamma\left(\frac{2}{k}\right)\Gamma\left(\frac{1}{k}\right)^{-1/2}\Gamma\left(\frac{3}{k}\right)^{-1/2} \tag{17}$$

where $\mu = E(r)$ and σ are the expected value and the standard deviation of return r, λ is a skewness parameter, *sign* is the sign function, and $\Gamma(.)$ is the gamma function. The scaling parameters k and λ obey the following constraints $k > 0$ and $-1 < \lambda < 1$. The parameter k controls the height and tails of the density function and the skewness parameter λ controls the rate of descent of the density around the mode of r, where mode(r) = $\mu - \delta\sigma$. In the case of positive skewness ($\lambda > 0$), the density function is skewed to the right. This is because for values of $r < \mu - \delta\sigma$, the return variable r is weighted by a greater value than unity and for values of $r > \mu - \delta\sigma$ by a value less than unity. The opposite is true for negative λ. Note that λ and δ have the same sign, thus, in case of positive skewness ($\lambda > 0$), the mode(r) is less than the expected value of r. The parameter δ is Pearson's skewness $[\mu - \text{mode}(r)]/\sigma = \delta$.

The SGED distribution reduces to the GED for $\lambda = 0$, the Laplace distribution for $\lambda = 0$ and $k = 1$, the normal distribution for $\lambda = 0$ and $k = 2$, and the uniform distribution for $\lambda = 0$ and $k = \infty$.

The SGED parameters are estimated by maximizing the log-likelihood function of r_t with respect to the parameters μ, σ, k, and λ:

$$LogL(\mu,\sigma,k,\lambda) = n\ln C - n\ln\sigma - \frac{1}{\theta^k\sigma^k}\sum_{t=1}^{n}\left(\frac{\left|r_t - \mu + \delta\sigma\right|^k}{\left[1 + sign(r_t - \mu + \delta\sigma)\lambda\right]^k}\right) \tag{18}$$

where C, θ, and δ are given by equations (13)-(15), *sign* is the sign of the residuals ($r_t - \mu + \delta\sigma$), n is the sample size, and ln is the natural logarithm.

2.2 Catastrophic Value at Risk (VaR) Estimates Using the GPD and the SGED

We estimate the entire return distribution under the two alternative assumptions – the normal and the SGED. Figure 2 presents the monthly parameter estimates for the SGED consisting of four moments (mean plotted in Figure 2A, standard deviation in Figure 2B, skewness in Figure 2C and kurtosis in Figure 2D).

The traditional VaR models assume that the probability distribution of log-price changes (log-returns) is normal. However, our results reject that hypothesis. Thus, we must derive alternative VaR models based on the GPD and SGED parameters.

In continuous time diffusion models, (log)-stock price movements are described by the following stochastic differential equation,

$$d\ln P_t = \mu_t dt + \sigma_t dW_t \tag{19}$$

where W_t is a standard Wiener process with zero mean and variance of dt, μ_t and σ_t are the time-varying drift and diffusion parameters of the geometric Brownian motion. In discrete time, equation (19) yields a return process:

$$\ln P_{t+\Delta} - \ln P_t = R_t = \mu_t \Delta t + \sigma_t z \sqrt{\Delta t} \tag{20}$$

where Δt is the length of time interval in which the discrete time data are recorded and $\Delta W_t = z\sqrt{\Delta t}$ is the Wiener process with zero mean and variance of Δt.

The critical step in calculating VaR measures is the estimation of the threshold point defining what variation in returns r_t is considered to be extreme. Let Φ be the probability that r_t is less than the threshold ϑ. That is,

$$\Pr(r_t < \vartheta) = \Pr\left(z < a = \frac{\vartheta - \mu_t \Delta t}{\sigma_t \sqrt{\Delta t}} \right) = \Phi \tag{21}$$

where $\Pr(\cdot)$ is the underlying probability distribution. In the traditional VaR model Φ=1%, a= –2.326,

$$\vartheta_{Normal} = \mu_t \Delta t - 2.326\ \sigma_t \sqrt{\Delta t}\ . \tag{22}$$

The risk manager, who has exposure to a risk factor r_t, needs to know how much capital to put aside to cover at least the fraction $1-\Phi$ of daily losses during a year. For this purpose, the risk manager must first determine a threshold ϑ so that the event ($r_t < \vartheta$) has a probability Φ under $\Pr(\cdot)$. The standard approach does this by using an explicit distribution that is in general the normal distribution. An alternative approach is to use a cumulative probability distribution $F(\vartheta)$ based on one of the extreme value and flexible probability distributions, and then solve for ϑ to obtain the threshold, i.e.,

$$\vartheta = F^{-1}(1-\Phi). \tag{23}$$

As shown in Bali (2003), the GPD distribution yields the following VaR threshold:[11]

$$\vartheta_{GPD} = \mu + \left(\frac{\sigma}{\xi}\right)\left[\left(\frac{\Phi N}{n}\right)^{-\xi} - 1\right] \tag{24}$$

where n and N are the number of extremes and the number of total data points, respectively. Once the location (μ), scale (σ), and shape (ξ) parameters of the GPD distribution are estimated one can find the VaR threshold, ϑ_{GPD}, based on the choice of confidence level (Φ).

There is substantial empirical evidence that the distribution of stock returns shows high peaks, fat tails and more outliers on the left tail. To account for skewness and kurtosis in the data, we use the skewed generalized error distribution (SGED) that account for the non-normality of returns and relatively infrequent events. As presented in Bali and Theodossiou (2003), the VaR threshold is computed using

$$\vartheta_{SGED} = \mu\Delta t + a\sigma\sqrt{\Delta t}\ , \tag{25}$$

where a is the cut-off for the standardized cdf associated with probability 1–Φ, i.e., $F(a)=1-\Phi$, and μ and σ are the mean and standard deviation parameters of the SGED density.

Using equations (24) and (25), we estimate the monthly Value at Risk (VaR) at the 99% confidence intervals (1% VaR) for the GPD and SGED parameters. Figure 3 compares the VaR results by deducting the GPD estimate from the SGED estimate. During the early period (1973-1983), the VaR estimates using the two methodologies appear to be quite similar. However, as catastrophic risk increases (decreases in 1% VaR), the methodologies diverge in their estimates. In general, the SGED methodology offers higher estimates of VaR, with prominent outliers in which the SGED VaR estimates are much lower than the GPD estimates.[12] Thus, methodological differences appear to become more important during periods when accurate risk estimates are most crucial. In Section 3, we incorporate a cyclical component into the value at risk estimates obtained using the two different methodologies.

3. Measuring the Importance of Cyclical Factors in Catastrophic Risk Measures

To test for cyclicality in the catastrophic risk measures defined in Sections 1 and 2, we gathered monthly data on macroeconomic, systemic risk, and regulatory factors from a wide variety of data sources.[13] The variables can be broadly classified into seven categories: macroeconomic (including GDP, unemployment statistics, the University of Michigan survey on consumer sentiment, business bankruptcies, industrial production and NBER-marked recessions), foreign exchange rates (for the major currencies – the Japanese yen, the German mark and the British pound sterling in terms of US dollars),[14] equity market indices (for Canada, France, Italy, Germany, Japan, the UK and the US), consumer price indices (for Japan, Germany, the UK and the US), interest rates (for long and short government bonds, Aaa-rated corporate bonds and Baa-rated corporate bonds), money supply figures (M2 for Japan, Germany, the EU, the UK and the US), and regulatory dummy variables (for the passage of the Depository Institutions Deregulatory and Monetary Control Act in March 1980, the FDIC Improvement Act in December 1991, the first Basel Capital Accord in December 1992, the Riegle-Neal Interstate

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[11] For alternative extreme value approaches to estimating VaR, see Longin (2000) and McNeil and Frey (2000).

[12] Comparisons using the 0.5% VaR and the 5% VaR yielded similar results to those shown in Figure 3.

[13] We measure the impact of economic and financial factors directly on monthly risk profiles. In contrast, there is a literature that incorporates systemic risk considerations by altering the variance-covariance matrix underlying returns. However, this may jeopardize the properties (e.g., invertibility) of the historical variance covariance matrix. See Kyle and Xiong (2001), Kodres and Pritzker (2002), Longin and Solnik (2001) and Rigobon and Forbes (2002).

[14] There were not enough monthly time series observations to use the Euro/US dollar exchange rate, adopted in January 1999, but we incorporate the Euro/US dollar exchange rate into the DM/US dollar exchange rate series after January 1999.

Banking and Branching Efficiency Act in September 1994, and the Gramm-Leach-Bliley Act in November 1999).[15] Panels A and B of Table 1 provide the source of data and the descriptive statistics for each of the 43 macroeconomic, cyclical factors.

3.1 Modeling Cyclical Components in the Catastrophic Risk Measures

We utilized the results from Sections 1 and 2 to test for cyclicality in our catastrophic risk measures. That is, in Section 1 we estimate catastrophic risk using Extreme Value Theory with the Generalized Pareto Distribution (GPD) for the lowest 10% of equity returns for financial institutions in each month of our sample period 1973-2001. That analysis generates three catastrophic risk estimates: the location parameter (the mean of the extremes), the scale parameter (related to the standard deviation of the extremes) and the shape or tail thickness parameter (measuring kurtosis in the extremes).[16] Hereinafter we denote these three risk measures respectively as μ-*GPD,* σ-*GPD,* and ξ-*GPD.*

In Section 2, we represent the entire return distribution using the Skewed Generalized Error Distribution (SGED), after first rejecting the hypothesis of normality for almost all months in our sample. The SGED generates four parameter measures: mean, standard deviation, kurtosis and skewness, hereinafter denoted μ-*SGED,*σ-*SGED,* ξ-*SGED,* and λ-*SGED,* respectively. Using the derivations described in Section 2.2 for the GPD and SGED parameters, we define the Value at Risk (VaR) at the 1% level as *VaR1%-GPD* and *VaR1%-SGED*, respectively.

We conducted the regression analysis using all 43 macroeconomic variables, but present only a representative subset in Tables 2A and 2B.[17] The results are consistent with significant levels of procyclicality in catastrophic VaR. For example, the positive and significant coefficients on the NBER

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[15] Although many other regulatory regime shifts occurred over the period 1973-2001, these five were viewed to be the most significant in terms of their impact on catastrophic risk in the financial services industry. The DIDMCA removed interest rate ceilings on deposits, authorized interest-bearing checking accounts (NOW and MMDA accounts), introduced uniform reserve requirements, increased deposit insurance coverage and expanded thrift powers. The FDICIA introduced prompt corrective action to require regulators to intervene when bank capital falls below certain thresholds, phased in risk-based deposit insurance premiums, limited "too big to fail" bailouts and forbearance by regulators, and extended federal regulation over foreign banks. The Basel Capital Accord created an internationally level playing field of capital requirements that were risk-adjusted and that included a capital charge for off-balance sheet activities. The Interstate Banking Act permitted bank holding companies to expand across state lines. The GLBA removed the Glass-Steagall Act restrictions on consolidation of banking, insurance and securities activities into a single holding company, thereby creating the financial holding company structure.

[16] Bali and Neftci (2003) indicate that the mean of the GPD can be measured by the estimated μ-*GPD* location parameter. They also show that the kurtosis of the extremes is largely determined by the estimated ξ-*GPD* and the standard deviation is a function of both the σ-*GPD* and the ξ-*GPD* parameters.

[17] First, we run a univariate OLS regression for each of the 43 macroeconomic variables. Second, we compute the correlation coefficients for all independent variables. To alleviate the problem of multicollinearity in our regression analysis, we omit those variables that are highly correlated with the most consistently significant cyclical factors. The final regressions are run for a selected number of cyclical variables that have low correlations with other variables. Results for the full panel of cyclical variables are available upon request.

dummy variable (equals 1 in recession, 0 otherwise) of 0.030 for *VaR1%-GPD* in Table 2A (significant at the 10% level) and 0.028 *VaR1%-SGED* in Table 2B (significant at the 5% level) suggest that catastrophic risk increases in recessions. A similar interpretation can be applied to the VaR-regression coefficients on the index of US industrial production. While the NBER recession dummy variable is a lagging indicator of economic conditions, the industry index is a leading indicator. Peaks in the index indicate turning points in the business cycle.[18] Thus, the positive coefficients on the industry index variable for the VaR regressions, 0.006 (significant at the 1% level) in Table 2A and 0.004 (significant at the 1% level) in Table 2B, are consistent with evidence of forward-looking procyclicality in catastrophic VaR. Comparing Tables 2A and 2B shows the robustness of this result. The relationships between both measures of 1% VaR and the macroeconomic variables are quite similar, both quantitatively and qualitatively.

The procyclicality found in the catastrophic VaR is also evidenced in the distributional risk parameters. For example, the negative and significant coefficients on the mean variables (μ-*GPD* in Table 2A and μ-*SGED* in Table 2B) are consistent with a negative (leftward) shift in the return distribution during economic downturns.

The regulatory environment also plays a role in determining the financial firms' catastrophic risk exposures. For example, implementation of the Basel Capital Accord in 1992 and passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act in 1994 are consistent with a significant (at the 5% level or better) reduction in 1% VaR measured using both the GPD and the SGED approaches. Moreover, passage of the DIDMCA of 1980 significantly (at the 1% level) reduced *VaR1%-GPD,* but this was insignificant for *VaR1%-SGED*. Moreover, the Japanese discount rate variable can be viewed as a proxy for easing/tightening of the environment of monetary and financial restrictions in Japan. The period of a falling Japanese discount rate corresponds to a liberalization of the Japanese financial environment in the wake of the Big Bang decontrols and attempts to rescue the troubled Japanese banking system. The positive and significant (at the 1% level) coefficients on the *RMBANK_a_JP* for both 1% VaR regressions is consistent with an increase in catastrophic risk during this volatile period.

4. Measuring Operational Risk

Before we can estimate operational risk, we must first define it; something easier said than done. The definitions range from the very narrow (regulatory approach) to extremely broad classifications. For example, Kingsley et al. (1998) define operational risk to be the "risk of loss caused by failures in

[18] The industry index variable has a correlation of –0.19 (significant at the 1% level) with the NBER dummy variable.

operational processes or the systems that support them, including those adversely affecting reputation, legal enforcement of contracts and claims." (page 3). Often this definition includes both strategic risk and business risk. That is, operational risk arises from breakdowns of people, processes and systems (usually, but not limited to technology) within the organization. Strategic and business risk originate outside of the firm and emanate from external causes such as political upheavals, changes in regulatory or government policy, tax regime changes, mergers and acquisitions, changes in market conditions, etc.

However, the Basel Committee on Banking Supervision excludes strategic and business risk from the definition proposed in the New Capital Accord. That is, BIS (September 2001) defines operational risk to be "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events." Explicitly excluded from this definition are systemic risk, strategic and reputational risks, as well as all indirect losses or opportunity costs, which may be open-ended and huge in size compared to direct losses.

We utilize the more expansive definition of operational risk. Indeed, we define operational risk as a residual measure. After all the identifiable sources of risk (credit risk, interest rate risk, exchange rate risk, equity price risk, etc.) are accounted for, the remainder is defined as operational risk. This sidesteps the difficult problem of modeling business activities on a micro level.[19]

We estimate the residual operational risk measure for each financial institution using a monthly time series over the period 1973-2001 for all firms in our sample with at least 100 monthly equity returns.[20] For each of these firms, we estimated the following OLS regression:[21]

$$r_t = \alpha_0 + \alpha_1 \Delta x_{1t} + \ldots + \alpha_{22} \Delta_{22t} + \beta r_{t-1} + \varepsilon_t \qquad (26)$$

where r_t and $r_{t\text{-}1}$ are the monthly and 1-month lagged equity returns on each of the financial firms in our sample over the period t = March 1973 through December 2001;[22] Δx_{it}, (i = 1, 2, …, 22), is the first order difference of the 22 variables used to estimate credit risk, interest rate risk, exchange rate risk and market risk.[23] Nineteen of these variables are taken from the macro variables defined in Table 1 and are grouped by risk source as follows:[24]

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[19] Ebnother et al. (2003) perform a case study that expends considerable resources to model 103 production processes, but can only explain a small portion of the firm's VaR, despite the high cost of defining and maintaining data about the operational processes.

[20] There were 38 firms with only 100 monthly observations. The average number of months for any individual financial firm in our sample was 178. The maximum number was 348 months over the entire sample period of January 1973 – December 2001.

[21] This model is the reduced form of a lagged regression model with an assumed one month lag.

[22] Because of the one month lag in equation (26), we could not estimate the model for the first quarter of 1973 and thus do not present results for January and February 1973.

[23] Each variable has 348 monthly observations over the sample period with the exception of RMGBS_a_UK (the 91 day UK Treasury bill rate), which was missing for 3 months.

[24] The three firm specific credit risk measures are taken from quarterly Compustat.

Overall Credit Risk Measure:
R_{AAA}-R_{BBB} = the spread between the AAA and the BBB corporate bond yield.

Firm Specific Credit Risk Measures:
Market value of equity/Book value of assets = 1 – leverage ratio.
Net income/sales.
Log of book value of total assets.

Interest Rate Risk Measures:
R_3MTB=3 month US Treasury bill rates.
R_10YTB=10 year US Treasury bond rates.
RM1B3S_a_UZ=3 month Euribor rates.
RMGB10Y_a_GY=10 year German Treasury bond rates.
RMBANK_a_JP=Discount rate in Japan.
RMGBL_a_JP=Long Japanese bond rates.
RMGBS_a_UK=91 day UK Treasury bill rates.
RMGBL_a_UK=10 year UK Treasury bond rates.

Exchange Rate Risk Measures:
Exgeus=Deutschemark/US dollar exchange rate.[25]
Exukus=British pound/US dollar exchange rate.
Exjpus=Japanese yen/US dollar exchange rate.

Market Risk Measures:
FPS6CA=Equity Index Canada.
FPS6FR=Equity Index France.
FPS6IT=Equity Index Italy.
FPS6JP=Equity Index Japan.
FPS6UK=Equity Index UK.
FPS6WG=Equity Index Germany.
SPINDX=S&P 500 Index.

The residual term, ε_t, from equation (26), is the measure of operational risk used in this analysis. We have 122,377 observations with the number of firms in any month ranging from 111 to 521.[26] A considerable portion of the raw returns for financial firms can be attributed to a return for operational risk exposure. On average, the ratio of residual (operational risk) to total equity returns is 66%, with considerable monthly variance.[27] This suggests that financial firms have become rather adept at hedging their market and even credit risk exposures, but that operational risk exposure has been left relatively

[25] After January 1999, the DM/US dollar exchange rate was replaced by the euro/US dollar exchange rate by calculating an imputed DM/US dollar exchange rate as follows: (DM/euro as of December 1998) x (euro/US$ as of each month starting in January 1999) = imputed DM/US$ for each month in the sample period after the adoption of the euro.
[26] We obtained qualitatively similar results when we performed a similar analysis by estimating equation (26) omitting the COMPUSTAT firm specific measures of credit risk. For that analysis, we had a total of 355,586 (rather than 122,377) observations.

unmanaged. This may be the result of the lag in the development of operational risk measurement models, as well as the less developed state of the catastrophic and operational risk derivatives market.[28]

In recent years, there has been an explosive growth in the use of derivatives. For example, as of December 2000, the total (on-balance-sheet) assets for all US banks was $5 trillion and for Euro area banks over $13 trillion. The value of non-government debt and bond markets worldwide was almost $12 trillion. In contrast, global derivatives markets exceeded $84 trillion in notional value [see Rule (2001)]. BIS data show that the market for interest rate derivatives totaled $65 trillion (in terms of notional principal), foreign exchange rate derivatives exceeded $16 trillion and equities almost $2 trillion.[29] The young and still growing credit derivatives market has been estimated at US$1 trillion as of June 2001. By comparison to these other derivatives markets, the market for operational risk derivatives is still in its infancy.

Cat bonds are examples of derivatives used to hedge operational risk. The earliest cat bonds were typically linked to a single risk. However, currently more than 65 percent of all new issues link payoffs to a portfolio of catastrophes. During April 2000 to March 2001, 11 percent of all newly issued cat bonds had sublimits that limited the maximum compensation payment per type of risk or per single catastrophe within the portfolio. Despite this limitation, the introduction of cat bonds allows access to a capital market that has the liquidity to absorb operational risk that is beyond the capacity of traditional insurance and self-insurance vehicles. Since cat bonds are privately placed Rule 144A instruments, most investors are either mutual funds/investment advisors or proprietary/hedge funds, accounting for 50 percent of the market in terms of dollar commitments at the time of primary distribution [see Schochlin (2002)]. The remainder of the investors consisted of reinsurers/financial intermediaries (21 percent), banks (8 percent), non-life insurers (4 percent) and life insurers (17 percent of the new issues market).

In order to examine the distribution of operational risk across types of financial intermediaries, Figures 4A, 4B and 4C divide the sample of financial firms into three groups: depository institutions (SIC codes 60XX, 66XX and 6712), insurance companies (SIC codes 63XX and 64XX) and securities firms (all other 6XXX-level SIC codes). In keeping with their roles as residual insurers of risk (e.g., as purchasers of cat bonds), Figure 4B shows that the insurance industry absorbed more operational risk than did securities firms over the 1973-2001 period. The average ratio of residual to raw equity returns for

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[27] The range of the ratios is not necessarily between 0 and 1 if, for example, the raw return for a particular monthly equity return is very small or negative whereas the 22 risk variables imply a high positive return, then the residual will be a large negative number, resulting in a ratio with absolute value exceeding one.
[28] For a discussion of the state of the art in operational risk measurement and management using derivatives, see chapter 5 of Allen, Boudoukh and Saunders (2003).
[29] Comprehensive global data on the size of OTC derivatives markets do not exist. Rule (2001) estimates the size of the market using Office of the Comptroller of the Currency data showing that US commercial banks held $352

insurance companies is 66.8% as compared to 64.7% for securities firms. In contrast, depository institutions (Figure 4A) have an average ratio of residual to raw equity returns of 68.4%. This is consistent with moral hazard implications of the government safety net that may induce banks to take on additional risk exposures. However, the standard deviation of the monthly operational risk ratio was lowest for depository institutions. The standard deviation for securities firms was 9.0%, the standard deviation for insurance companies was 7.0% and for banks only 5.6%. Figures 4A, 4B, and 4C show that securities firms experienced large operational risk losses during the market crashes of 1987 and 2000. However, the greatest volatility in the operational risk ratio was for insurance companies, consistent with their roles as net insurers of operational risk.

We use the monthly residual operational risk measures derived from equation (26) to re-estimate the tails of the loss distribution. Operational risk events can be divided into high frequency/low severity (HFLS) events that occur regularly, in which each event individually exposes the firm to low levels of losses. In contrast, low frequency/high severity (LFHS) operational risk events are quite rare, but the losses to the organization are enormous upon occurrence. An operational risk measurement model must incorporate both HFLS and LFHS risk events. There is an inverse relationship between frequency and severity so that high severity risk events are quite rare, whereas low severity risk events occur rather frequently. In the next sections, we utilize both the GPD and the SGED models (described in Sections 1 and 2) to examine the tails of our derived operational risk measures.

4.1 Operational Risk – The GPD Approach

We use the methodology presented in Section 1.2 to re-estimate the three GPD location, scale and tail thickness parameters (denoted μ*-ORGPD,* σ*-ORGPD,* and ξ*-ORGPD*, respectively) using the operational risk residuals and then use the methodology in Section 2.2 to define the GPD operational Value at Risk (VaR) at the 1% level, denoted *VaR1%-ORGPD*. Figure 5 compares the 1% operational VaR measures using the GPD to the catastrophic 1% VaR measures using the GPD (as calculated in Section 2.2). The plot of the monthly VaR shows that the operational risk VaR measures are less negative (have lower loss levels) than the VaR measures obtained for catastrophic risk for most months in the sample period from 1973-2001. Indeed, on average, the 1% VaR operational loss level is 2.4% less than the 1% VaR catastrophic loss level. However, there are instances in which the residual VaR loss levels exceed the catastrophic risk VaR exposures (i.e., the comparison value is negative). Although this was most pronounced during January 1975, when the operational VaR loss levels exceeded the catastrophic

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billion notional credit derivatives outstanding on March 31, 2001 pro-rated for US banks' share using a British Bankers Association Survey showing that the global market totaled $514 billion in 1999.

VaR levels by their greatest amounts (over 18% for all VaR measures), it occurred intermittently throughout the sample period.

4.2 Extreme Operational Risk – The SGED Approach

Using the monthly residual operational risk measures, we re-estimate the SGED using the methodology described in Section 2 for operational risk, thereby generating four parameter measures: mean, standard deviation, kurtosis and skewness for operational risk (denoted *μ-ORSGED, σ-ORSGED, ξ-ORSGED,* and *λ-ORSGED,* respectively). Using these parameter values, we then estimate the monthly 1% VaR (denoted *VaR1%-ORSGED*), shown in Figure 6 compared to the catastrophic risk *VaR1%-SGED* estimated in Section 2.2. Figure 6 shows that the operational risk VaR measures are less negative (have lower loss levels) than the catastrophic VaR measures obtained using raw returns. Indeed, on average, the 1% VaR operational loss level is 2.5% less than the 1% VaR catastrophic loss level.[30] These results are quite similar to those obtained using the GPD methodology described in Figure 5 above. Moreover, as for the *VaR1%-GPD* results, there are instances in which the SGED operational VaR level exceeds the SGED catastrophic VaR level, although the order of magnitude is less than observed for the GPD estimates of operational VaR levels.

Results from both the GPD and the SGED methodologies suggest that financial intermediaries are exposed to considerable amounts of residual operational risk. Operational risk management presents extremely difficult risk control challenges when compared to the management of other sources of risk exposure, such as market risk, liquidity risk and credit risk. The internal nature of the exposure makes both measurement and management difficult. Young (1999) states that "open socio-technical systems have an infinite number of ways of failing….The complexity of human behavior prevents errors from being pre-specified and reduced to a simple numerical representation" (p. 10). Operational risk is embedded in a firm and cannot be easily separated out. Thus, even if a hedge performs as designed, the firm will be negatively affected in terms of damage to reputation or disruption of business as a result of a low frequency, high severity operational risk event.

5. Cyclicality in Operational Risk Measures

In Section 4, we derived a residual measure of operational risk. In this section, we investigate the cyclical components of our operational risk measure. We examine the relationship between the operational risk measures and the cyclical factors presented in Table 1, which consist of monthly data on

[30] Similar results are obtained for 0.5%, 1.5%, 2%, and 2.5% catastrophic and operational VaR levels.

macroeconomic, cyclical, systemic risk, and regulatory factors. To replicate the regression analysis used for catastrophic risk on operational risk, we follow the methodology outlined in Section 3.1. Tables 3A and 3B present the regression results for a representative sample of macroeconomic variables using all seven of the GPD operational risk parameters and the SGED operational risk parameters, as well as the operational value at risk measures *VaR1%-ORGPD* and *VaR1%-ORSGED*.[31]

The results presented in Tables 3A and 3B again display considerable consistency across the GPD and SGED methodologies. Coefficients are similar in size, sign and statistical significance. There is also evidence of procyclicality in the operational value at risk measures. Although the NBER recession dummy variable is not statistically significant, the coefficient on the index of US industrial production is positive and statistically significant (at the 5% level or better) for both the *VaR1%-ORGPD* and *VaR1%-ORSGED* regressions (0.003 in Table 3A using the GPD methodology and 0.001 in Table 3B using the SGED methodology). Moreover, the coefficient on the 3 month US Treasury bill rate level (*R_3MTB*) is significantly (at the 1% level) negative for both the *VaR1%-ORGPD* and *VaR1%-ORSGED* regressions. This suggests that operational value at risk declines during the periods of a relatively tight monetary policy consistent with an overheated economy. Similarly, during periods of an easy monetary policy, generally coincident with economic downturns, the operational value at risk (*VaR1%-ORGPD* and *VaR1%-ORSGED*) increases.

The regulatory environment also impacts operational value at risk. As for catastrophic value at risk, the results in Tables 3A and 3B are consistent with significant (at the 5% level) decreases in operational value at risk following the implementation of the Basel Capital Accord in 1992 and the passage of the Interstate Banking Act in 1994.

Examining the individual risk parameters in Tables 3A and 3B provides additional evidence of procyclicality in operational risk exposures. The coefficients on the NBER recession dummy variable for the mean regressions (μ*-ORGPD* in Table 3A and μ*-ORSGED* in Table 3B) are significantly (at the 5% level) negative, suggesting that there is a negative (downward) shift in mean operational risk measures during economic recessions.

6. Conclusions

We examine the catastrophic risk of financial institutions and test for procyclicality. We utilize an extreme value approach (Generalized Pareto Distribution, GPD), as well as a generalized distributional approach (Skewed Generalized Error Distribution, SGED) to obtain estimates of catastrophic risk

[31] Before we measure cyclicality in operational risk measures using a series of OLS regressions, the same methodology described in footnote 17 is used to select the relevant macroeconomics variables associated with business cycle fluctuations.

parameters and 1% value at risk (VaR). We find evidence of procyclicality in the catastrophic VaR for financial institutions.

We define a new, residual operational risk measure and estimate the risk parameters using both the GPD and the SGED. We use these operational risk parameters to solve for the 1% operational VaR. Using our measure, we find that operational risk is quite significant, comprising approximately two thirds of the total equity returns of financial institutions. This paper presents the first evidence of procyclicality in operational risk measures.

Results are consistent across methodologies for both catastrophic and operational risk measures. Thus, we conclude that macroeconomic, systematic and environmental factors play a considerable role in influencing the risk of financial institutions. Models that ignore these factors are therefore fundamentally flawed. These results provide encouragement for further research into both catastrophic and operational risk measures that are conditioned on cyclical factors.

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Figure 1A. Location Parameter of the GPD (January 1973 - December 2001)

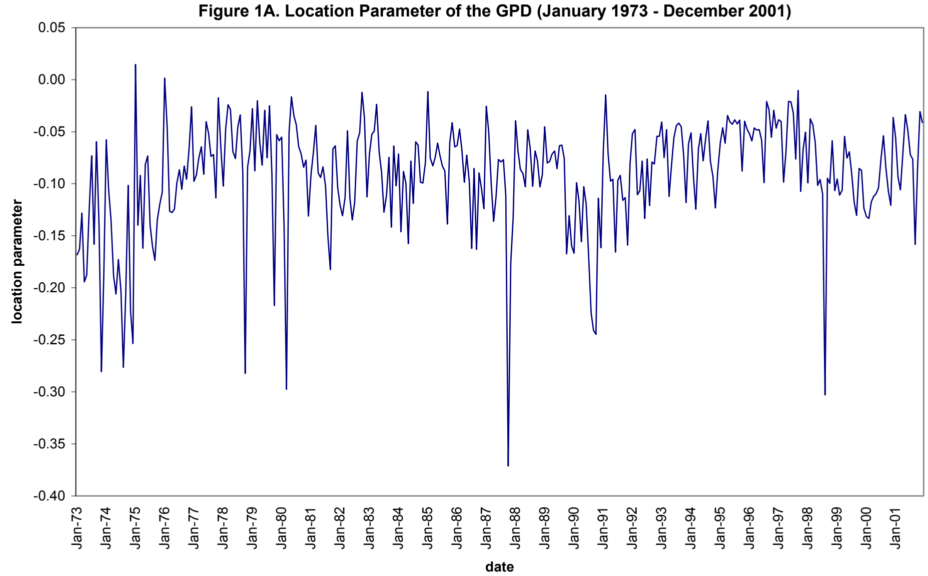


Figure 1B. Scale Parameter of the GPD (January 1973-December 2001)

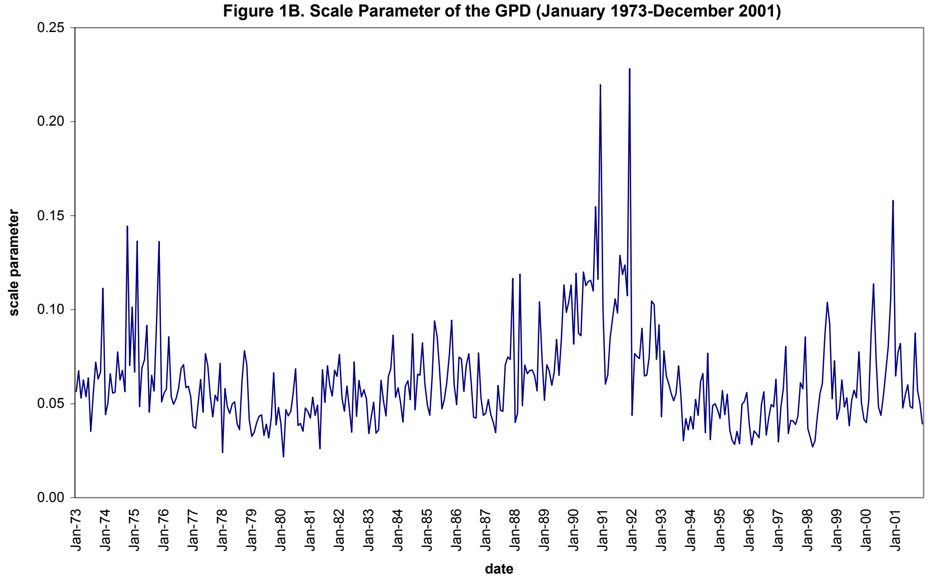
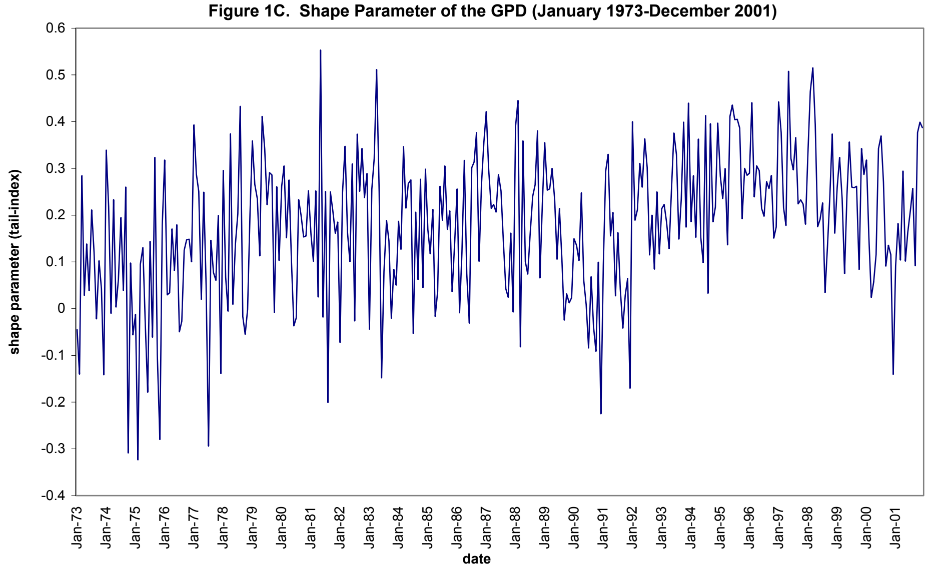


Figure 1C. Shape Parameter of the GPD (January 1973-December 2001)



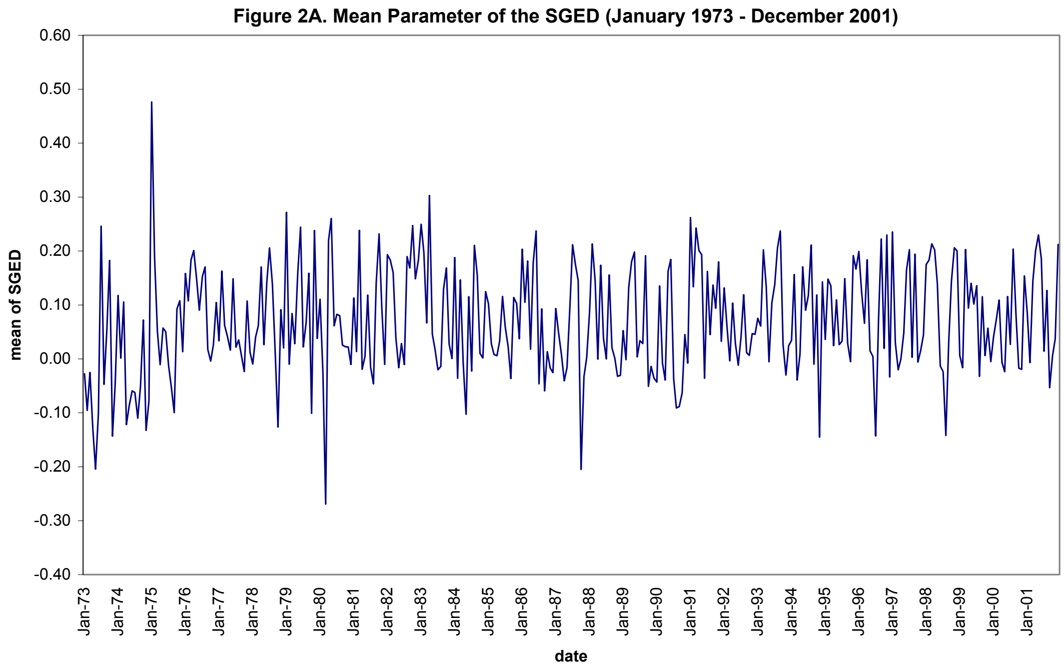


Figure 2A. Mean Parameter of the SGED (January 1973 - December 2001)
mean of SGED
0.60
0.50
0.40
0.30
0.20
0.10
0.00
-0.10
-0.20
-0.30
-0.40
Jan-73
Jan-74
Jan-75
Jan-76
Jan-77
Jan-78
Jan-79
Jan-80
Jan-81
Jan-82
Jan-83
Jan-84
Jan-85
Jan-86
Jan-87
Jan-88
Jan-89
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Jan-00
Jan-01
date

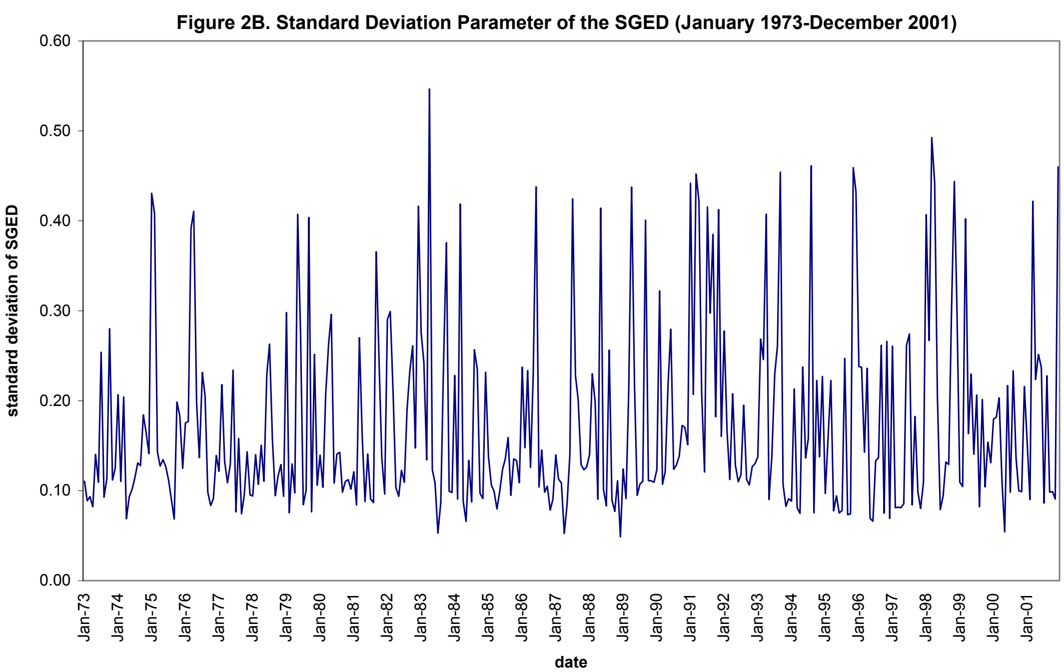


Figure 2B. Standard Deviation Parameter of the SGED (January 1973-December 2001)
standard deviation of SGED
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Jan-73
Jan-74
Jan-75
Jan-76
Jan-77
Jan-78
Jan-79
Jan-80
Jan-81
Jan-82
Jan-83
Jan-84
Jan-85
Jan-86
Jan-87
Jan-88
Jan-89
Jan-90
Jan-91
Jan-92
Jan-93
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99
Jan-00
Jan-01
date

Figure 2C. Skewness Parameter of the SGED (January 1973-December 2001)

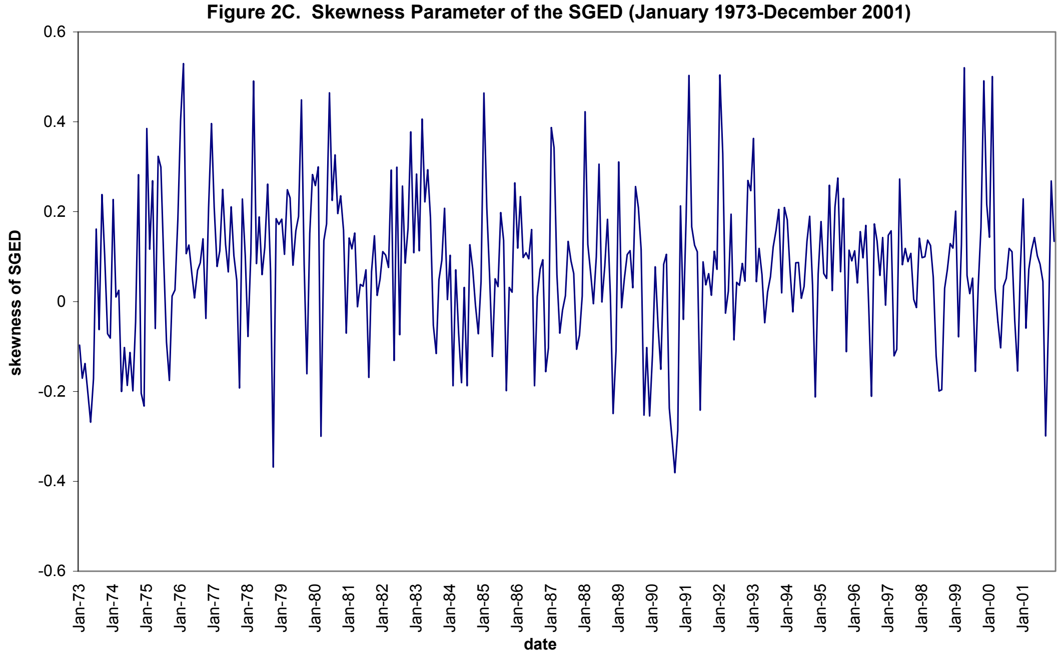


Figure 2D. Tail-Thickness Parameter of the SGED (January 1973-December 2001)

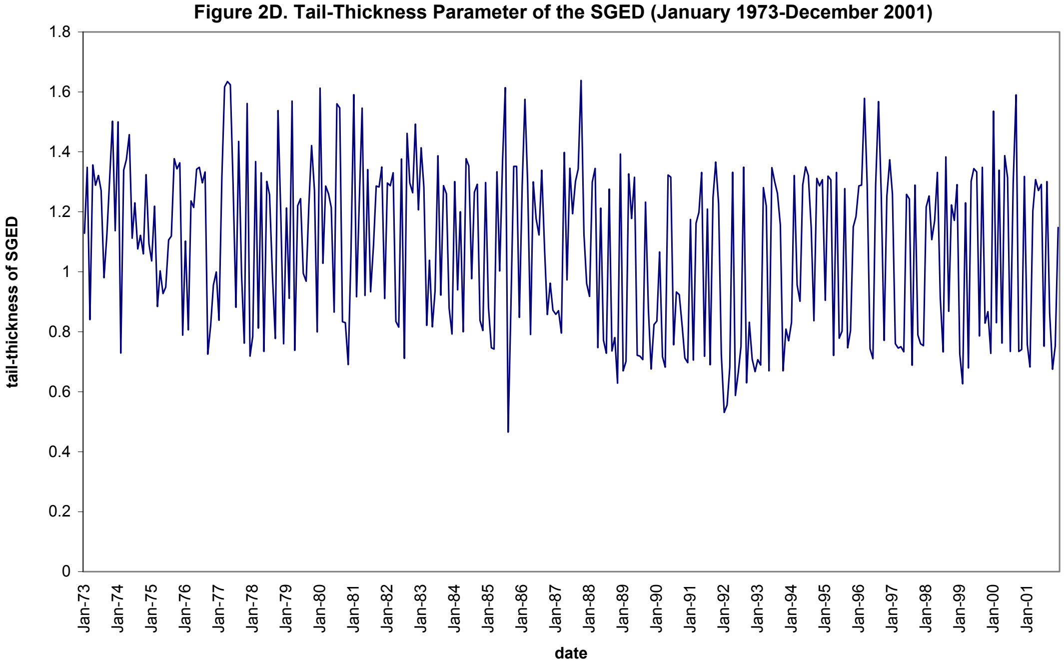


Figure 3A. 1% Catastrophic VaR Estimates of GPD and SGED

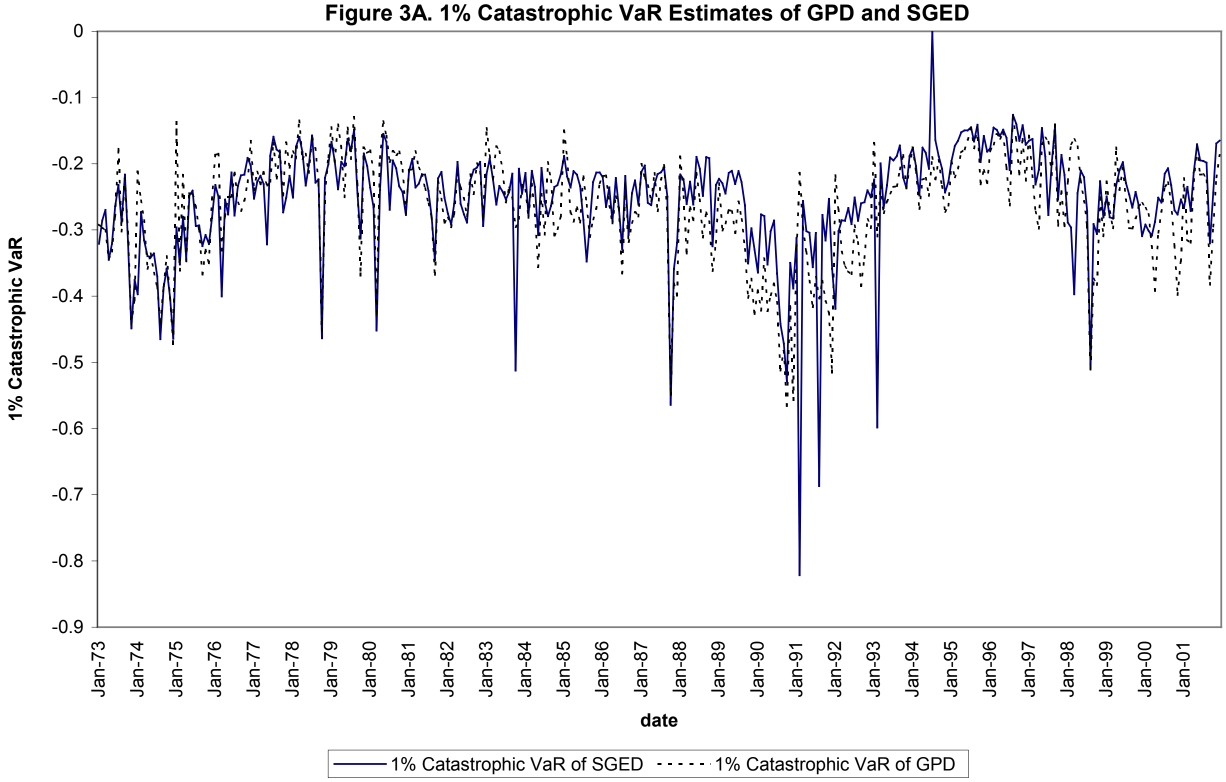


Figure 3B. Differences in 1% Catastrophic VaR Estimates: SGED minus GPD

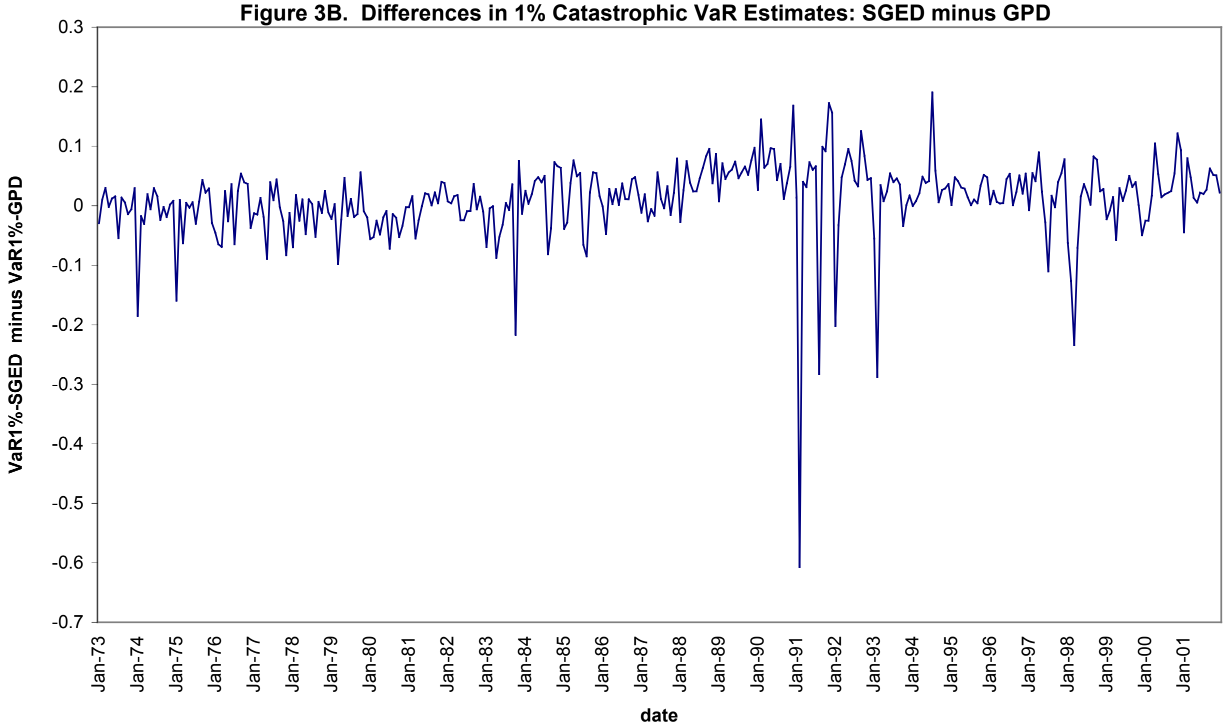


Table 1
Panel A. Sources of Data on Cyclical Factors

Variable Name	Variable Description	Data Source	Number of Obs.	Data Range
Consentiment	Consumer Sentiment University of Mich	Economagic	348	1973-2001
USunempl	US Unemployment Rate	Bureau of Labor Statistics	348	1973-2001
RsvAst	Aggregate Bank Reserve to Assets	Federal Reserve Bank Kansas City	264	1980-2001
BusBnkrpcy	No. of US Business Bankruptcies	Administrative Office of Courts	264	1980-2001
IndstryIndex	US Industrial Production	Global Insight (DRI)	348	1973-2001
exgeus	Dmark/US$ FX Rate	WRDS FX File	312	1973-1998
exukus	UK/US$ FX Rate	WRDS FX File	348	1973-2001
exjpus	JP/US$ FX Rate	WRDS FX File	348	1973-2001
FPS6CA	Equity Index Canada	DRI	348	1973-2001
FPS6FR	Equity Index France	DRI	348	1973-2001
FPS6IT	Equity Index Italy	DRI	348	1973-2001
FPS6JP	Equity Index Japan	DRI	348	1973-2001
FPS6UK	Equity Index UK	DRI	348	1973-2001
FPS6WG	Equity Ind.Germany	DRI	348	1973-2001
SPINDX	S&P 500 Index	CRSP Indices	348	1973-2001
CPI_JP	CPI Japan	Eurostat	275	1978-2000
CPI_UK	CPI UK	Eurostat	336	1973-2000
CPI_US	CPI US	Bureau of Labor Statistics	336	1973-2000
CPI_G	CPI Germany	Eurostat	336	1973-2000
R_3MTB	3 month US T-bills	Federal Reserve Bank of St. Louis - FRED	348	1973-2001
R_10YTB	10 yr US T-bonds	FRED	348	1973-2001
R_AAA	AAA bond rate	FRED	348	1973-2001
R_Baa	Baa bond rate	FRED	348	1973-2001
RMIB3S_a_UZ	3 mo.Euribor rate	DRI	348	1973-2001
RMGB10Y_a_GY	10 yr German T-bond	DRI	348	1973-2001
RMBANK_a_JP	Discount rate Japan	DRI	348	1973-2001
RMGBL_a_JP	Long Japanese bond	DRI	348	1973-2001
RMGBS_a_UK	91 day UK T-bill	DRI	345	1973-2001
RMGBL_a_UK	10 yr UK T-bond	DRI	348	1973-2001
M2SL	US M2 money supply	FRED	348	1973-2001
M2_a_JP	JP M2 money supply	DRI	348	1973-2001

Variable Name	Variable Description	Data Source	Number of Obs.	Data Range
M2NS_a_GY	German M2 money	DRI	264	1980-2001
M2_a_UK	UK M2 money	DRI	235	1982-2001
M2_a_UZ	EU M2 Money	DRI	264	1980-2001
JM2_a_UZ	M2 Index Eurozone	DRI	264	1980-2001
GDP_US	US GDP	Bureau Economic Analysis	348	1973-2001
DUM_DIDMCA	Depository Institution Deregulatory and Monetary Control Act dummy variable	constructed	348	1973-2001
DUM_FDICIA	FDIC Improvement Act dummy variable	constructed	348	1973-2001
DUM_Basel	Implementation of Basel I dummy var.	constructed	348	1973-2001
DUM_Interstate	Riegle-Neal Interstate Banking & Branching Efficiency Act var.	constructed	348	1973-2001
DUM_GLBA	Gramm-Leach-Bliley Act dummy var.	constructed	348	1973-2001
DUM_NBER	Recessions as marked by NBER dummy var	NBER website	348	1973-2001
RegDum	=1 for the first month of each of the 5 reg. changes above: DIDMCA, FDICIA, Basel, Interstate, and GLBA; 0 otherwise	constructed	348	1973-2001

Panel B. Descriptive Statistics for Cyclical Factors

Variable Name	Variable Description	Mean	Std. Dev.	Median	Minimum	Maximum
Consentiment	Consumer Sentiment University of Mich	85.92	13.29	89.3	51.7	112
USunempl	US Unempl. Rate	6.37%	1.48%	6.15%	3.8%	10.8%
RsvAst	Aggregate Bank Reserve to Assets	1.12%	0.37%	1.08%	0.54%	1.64%
BusBnkrpcy	No. of US Business Bankruptcies	4870	1191	4846	2577	9534
IndstryIndex	US Industrial Production	96.90	23.09	93.44	61.34	147.19
exgeus	Dmark/US$ FX Rate	DM 2.05/US$	DM 0.46	DM 1.87/US$	DM 1.38/US$	DM 3.30/US$
exukus	UK/US$ FX Rate	£0.59/US$	£0.10	£0.60/US$	£0.39/US$	£0.92/US$
exjpus	JP/US$ FX Rate	¥181.41/US$	¥68	¥152.37/US$	¥83.69/US$	¥305.67/US$
FPS6CA	Equity Index Canada	101.72	65.24	92.4	25	328.8
FPS6FR	Equity Index France	88.88	85.40	71.35	11.1	364.5
FPS6IT	Equity Index Italy	85.56	78.28	78.35	8.7	330.7
FPS6JP	Equity Index Japan	50.10	28.85	48.6	12.2	135
FPS6UK	Equity Index UK	99.50	83.67	84.05	6.2	299.5
FPS6WG	Equity Index Germany	108.85	105.65	77.15	22.3	452
SPINDX	S&P 500 Index	408.21	392.72	261.43	63.54	1517.68
CPI_JP	CPI Japan	103.68	11.67	104	76.09	118.2
CPI_UK	CPI UK	106.92	48.04	105.51	23.93	182
CPI_US	CPI US	103.63	36.34	103.08	39.63	161.8
CPI_G	CPI Germany	100.08	22.11	100.2	58.02	134.8
R_3MTB	3 month US T-bills	6.69%	2.69%	5.93%	1.69%	16.3%
R_10YTB	10 yr US T-bonds	8.24%	2.36%	7.76%	4.53%	15.32%
R_AAA	AAA bond rate	9.14%	2.09%	8.65%	6.22%	15.49%
R_Baa	Baa bond rate	10.23%	2.46%	9.75%	7.09%	17.18%
RMIB3S_a_UZ	3 mo.Euribor rate	8.63%	3.32%	8.54%	2.57%	18.92%
RMGB10Y_a_GY	10 yr German T-bond	7.25%	1.58%	7.18%	3.65%	10.83%
RMBANK_a_JP	Discount rate Japan	3.88%	2.56%	3.88%	0.1%	9%

Variable Name	Variable Description	Mean	Std. Dev.	Median	Minimum	Maximum
RMGBL_a_JP	Long Japanese bond	5.55%	2.35%	6.18%	0.82%	8.89%
RMGBS_a_UK	91 day UK gov	9.56%	3.22%	9.61%	3.89%	16.97%
RMGBL_a_UK	10 yr UK gov	10.02%	2.93%	10.02%	4.25%	16.34%
M2SL	US M2	$2682.54 b	$1238.50 b	$2782.14 b	$810.17 b	$5444.44 b
M2_a_JP	JP M2	¥363,836 b	¥181,964 b	¥353,573 b	¥82,303 b	¥656,794 b
M2NS_a_GY	German M2	DM1529.35 b	DM626.18 b	DM1498.85 b	DM679.4 b	DM2673.62 b
M2_a_UK	UK M2 money	£345.41 b	£148.75 b	£338.88 b	£114.60 b	£646.20 b
M2_a_UZ	EU M2 Money	EU2600.86 b	EU 991.67 b	EU2579.58 b	EU1071.05 b	EU4598.9 b
JM2_a_UZ	M2 Index EU	0.58	0.21	0.57	0.25	0.99
GDP_US	US GDP	$1691.94 b	$879.66 b	$1577.67 b	$446.13 b	$3384.31 b
DUM_DIDMCA	DIDMCA dummy var.	0.75			0	1
DUM_FDICIA	FDICIA dummy var.	0.35			0	1
DUM_Basel	Implementation of Basel I var.	0.31			0	1
DUM_Interstate	Riegle-Neal dummy var.	0.25			0	1
DUM_GLBA	Gramm-Leach-Bliley dummy	0.07			0	1
DUM_NBER	NBER recessions var	0.17			0	1
RegDum	New regs var.	0.01			0	1

Notes: The last column represents the frequency of significance of each variable in the stepwise OLS regressions on the various risk measures. A variable is included in the regression if its coefficient has a significance level of 10% or better. Regression results are presented in Tables 4a-k.

Table 2A. Regression Results from Catastrophic Risk Estimates of GPD

The full model is: *Risk Factor Variable*$_t$ = $\alpha_t + \beta_{1,t}I_{1,t} + \ldots + \beta_{n,,t}I_{n,,t} + \varepsilon_t$ where $I_{1,t} \ldots I_{n,t}$ are the cyclical factor variables listed in Table 1, n=1,…43, t=*January* 1973…*December* 2001. We present only a representative number of the cyclical factor variables in the table. The *Risk Factor Variable*$_t$ takes the value of the location, scale and tail thickness parameters of the GPD (*μ-GPD, σ-GPD,* and *ξ-GPD*, respectively) and the *VaR1%-GPD* catastrophic value at risk. Standard errors in parentheses. ***, **, * denote 1%, 5% and 10% levels of significance, respectively.

Variable Name	Location *μ-GPD*	Scale *σ-GPD*	Tail Thickness *ξ-GPD*	Value at Risk *VaR1%-GPD*
Intercept Term	0.227***	-0.070	-0.299	0.412***
	(0.075)	(0.048)	(0.534)	(0.106)
Consentiment	-0.0008**	-0.0002	0.004	-0.0009
	(0.0004)	(0.0003)	(0.003)	(0.0006)
IndstryIndex	-0.003***	0.001***	0.004	-0.006***
	(0.0008)	(0.0005)	(0.006)	(0.001)
SPINDX	0.00004	-0.000002	-0.0003	0.00006
	(0.00003)	(0.00002)	(0.0002)	(0.00005)
R_3MTB	-0.003	-0.001	-0.041***	0.004
	(0.002)	(0.001)	(0.013)	(0.003)
RM1B3S_a_UZ	0.002	0.001	-0.0002	-0.0004
	(0.002)	(0.001)	(0.016)	(0.003)
	-0.010***	0.007***	-0.017	-0.021***
RMBANK_a_JP	(0.003)	(0.002)	(0.024)	(0.005)
	0.002	-0.002*	0.032**	0.001
RMGBS_a_UK	(0.002)	(0.001)	(0.013)	(0.003)
DUM_DIDMCA	0.021**	-0.013*	-0.100	0.047***
	(0.011)	(0.007)	(0.077)	(0.015)
DUM_FDICIA	-0.015	0.0009	-0.036	-0.013
	(0.019)	(0.012)	(0.138)	(0.028)
DUM_Basel	0.030	-0.013	0.032	0.056**
	(0.018)	(0.012)	(0.131)	(0.026)
DUM_Interstate	0.039**	-0.013	0.090	0.071***
	(0.016)	(0.010)	(0.115)	(0.023)
DUM_GLBA	0.0003	0.004	-0.011	-0.010
	(0.015)	(0.010)	(0.109)	(0.022)
DUM_NBER	-0.030***	0.004	-0.006	-0.030*
	(0.011)	(0.007)	(0.078)	(0.016)
Adj. R-square	9.63%	10.89%	6.81 %	31.85%
# observations	342	342	342	342

Table 2B. Regression Results from Catastrophic Risk Estimates of SGED

The full model is: *Risk Factor Variable*$_t$ = $\alpha_t + \beta_{1,t}I_{1,t} + \ldots + \beta_{n,,t}I_{n,,t} + \varepsilon_t$ where $I_{1,t}\ldots I_{n,t}$ are the cyclical factor variables listed in Table 1, n=1,…43, t=*January* 1973…*December* 2001. We present only a representative number of the cyclical factor variables in the table. The *Risk Factor Variable*$_t$ takes the value of the mean, standard deviation, kurtosis and skewness parameters of the SGED (μ-*SGED*, σ-*SGED*, ξ-*SGED*, and λ-*SGED* respectively) and the *VaR1%-SGED* catastrophic value at risk. Standard errors in parentheses. ***, **, * denote 1%, 5% and 10% levels of significance, respectively.

Variable Name	Mean μ-SGED	Std. Dev. σ-SGED	Kurtosis ξ-SGED	Skewness λ-SGED	Value at Risk VaR1%-SGED
Intercept Term	0.297***	0.071***	1.541***	1.059***	0.199**
	(0.074)	(0.027)	(0.348)	(0.242)	(0.085)
Consentiment	-0.001***	-0.0006***	0.002	-0.004***	-0.0002
	(0.0004)	(0.0001)	(0.002)	(0.001)	(0.0005)
IndstryIndex	-0.002***	0.0004	-0.008**	-0.008***	-0.004***
	(0.0008)	(0.0003)	(0.004)	(0.003)	(0.0009)
SPINDX	0.00009***	0.00006***	0.0002	0.0003***	-0.00001
	(0.00003)	(0.00001)	(0.0002)	(0.0001)	(0.00004)
R_3MTB	-0.005***	-0.003***	0.042***	-0.006	0.001
	(0.002)	(0.0007)	(0.009)	(0.006)	(0.002)
RM1B3S_a_UZ	0.002	0.0009	-0.015	0.003	0.0003
	(0.002)	(0.0008)	(0.010)	(0.007)	(0.002)
	-0.006*	0.003***	0.040**	-0.030***	-0.017***
RMBANK_a_JP	(0.003)	(0.001)	(0.016)	(0.011)	(0.004)
	0.002	0.0004	-0.031***	0.012**	0.002
RMGBS_a_UK	(0.002)	(0.0006)	(0.009)	(0.006)	(0.002)
DUM_DIDMCA	0.039***	0.011***	0.089*	0.096***	0.017
	(0.011)	(0.004)	(0.050)	(0.036)	(0.012)
DUM_FDICIA	-0.021	-0.004	0.023	-0.043	-0.010
	(0.019)	(0.007)	(0.090)	(0.063)	(0.022)
DUM_Basel	0.012	-0.014**	-0.019	0.094	0.049**
	(0.018)	(0.007)	(0.086)	(0.059)	(0.021)
DUM_Interstate	0.031*	-0.012**	0.046	0.027	0.061***
	(0.016)	(0.006)	(0.075)	(0.052)	(0.018)
DUM_GLBA	0.004	-0.001	0.014	-0.048	0.001
	(0.015)	(0.005)	(0.071)	(0.049)	(0.017)
DUM_NBER	-0.030***	-0.004	0.111**	-0.093***	-0.027**
	(0.011)	(0.0004)	(0.051)	(0.035)	(0.012)
Adj. R-square	4.68%	46.40%	29.62%	4.83 %	32.53%
# observations	342	342	342	342	342

Figure 4A. Ratio of Operational Risk to Total Return: Depository Financial Intermediaries

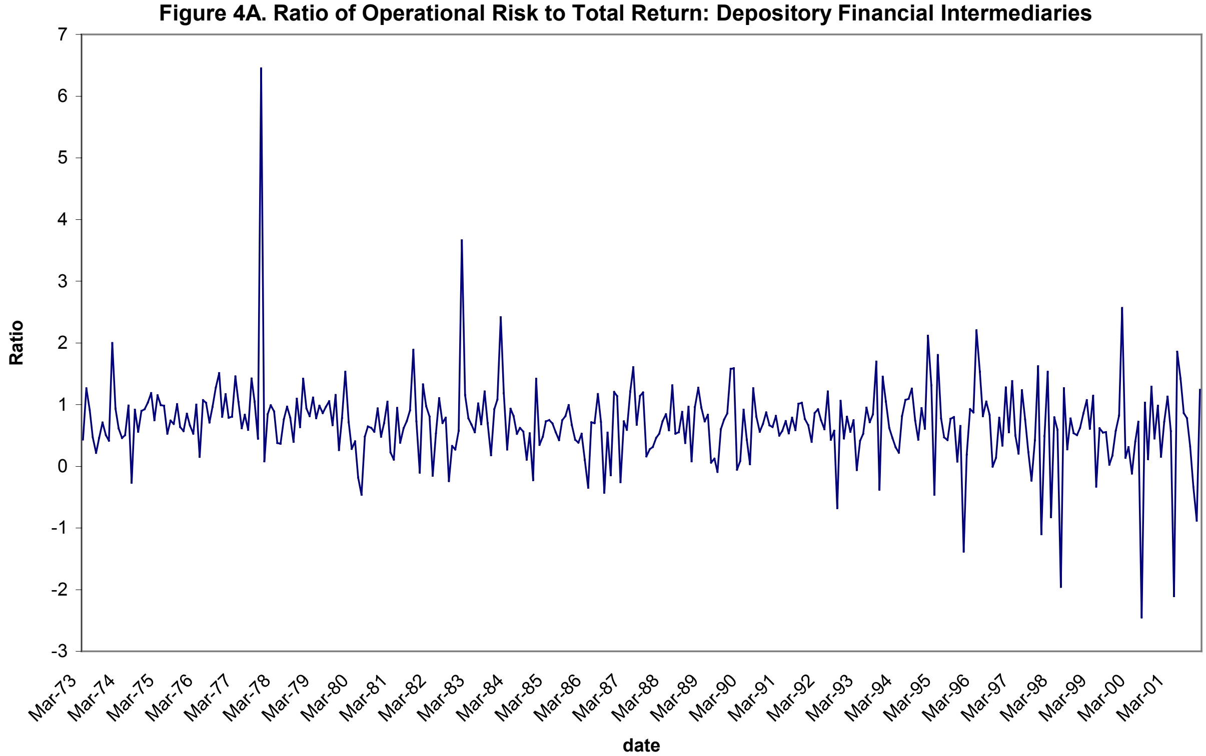
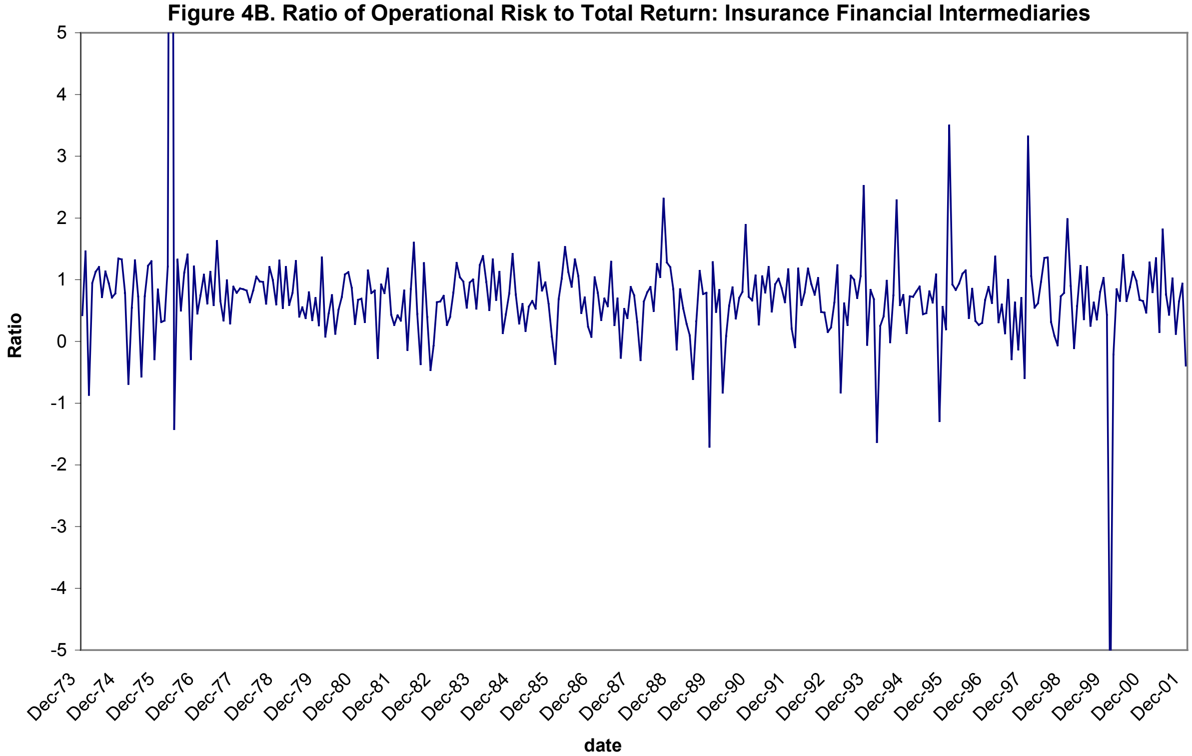


Figure 4B. Ratio of Operational Risk to Total Return: Insurance Financial Intermediaries



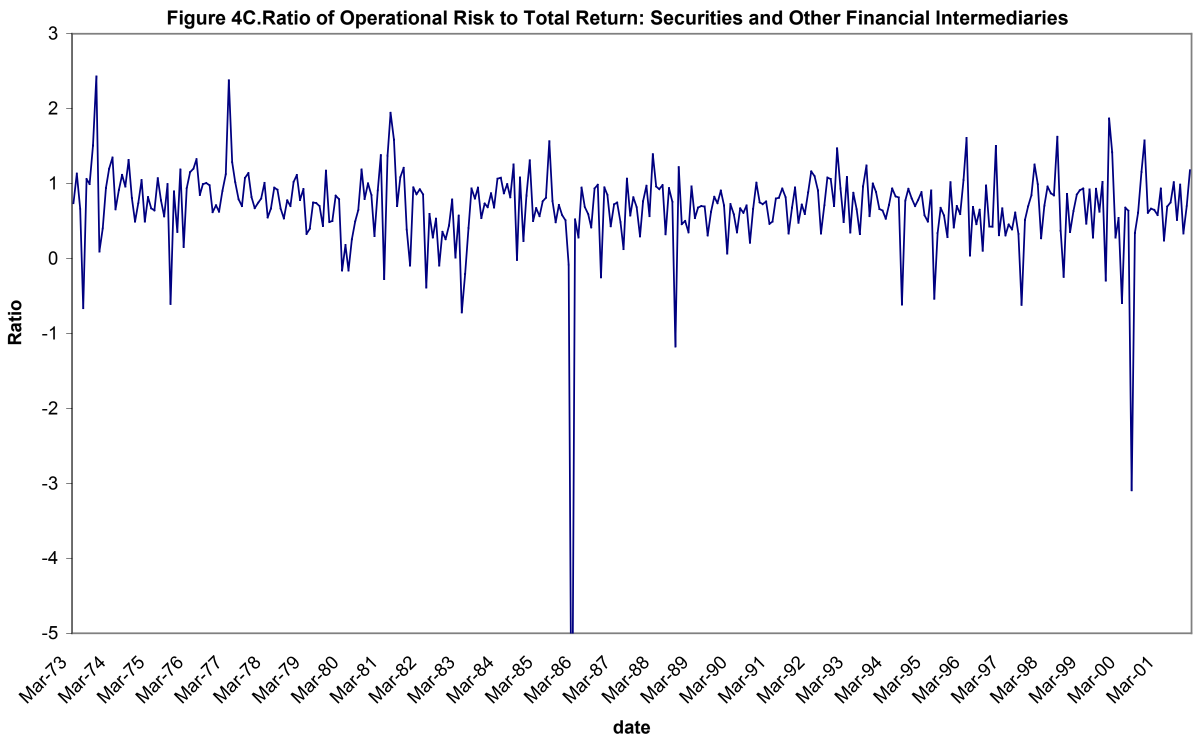


Figure 4C.Ratio of Operational Risk to Total Return: Securities and Other Financial Intermediaries
3
2
1
0
-1
-2
-3
-4
-5
Ratio
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Mar-74
Mar-75
Mar-76
Mar-77
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Mar-79
Mar-80
Mar-81
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Figure 5. Catastrophic and Operational 1% VaR Estimates of GPD

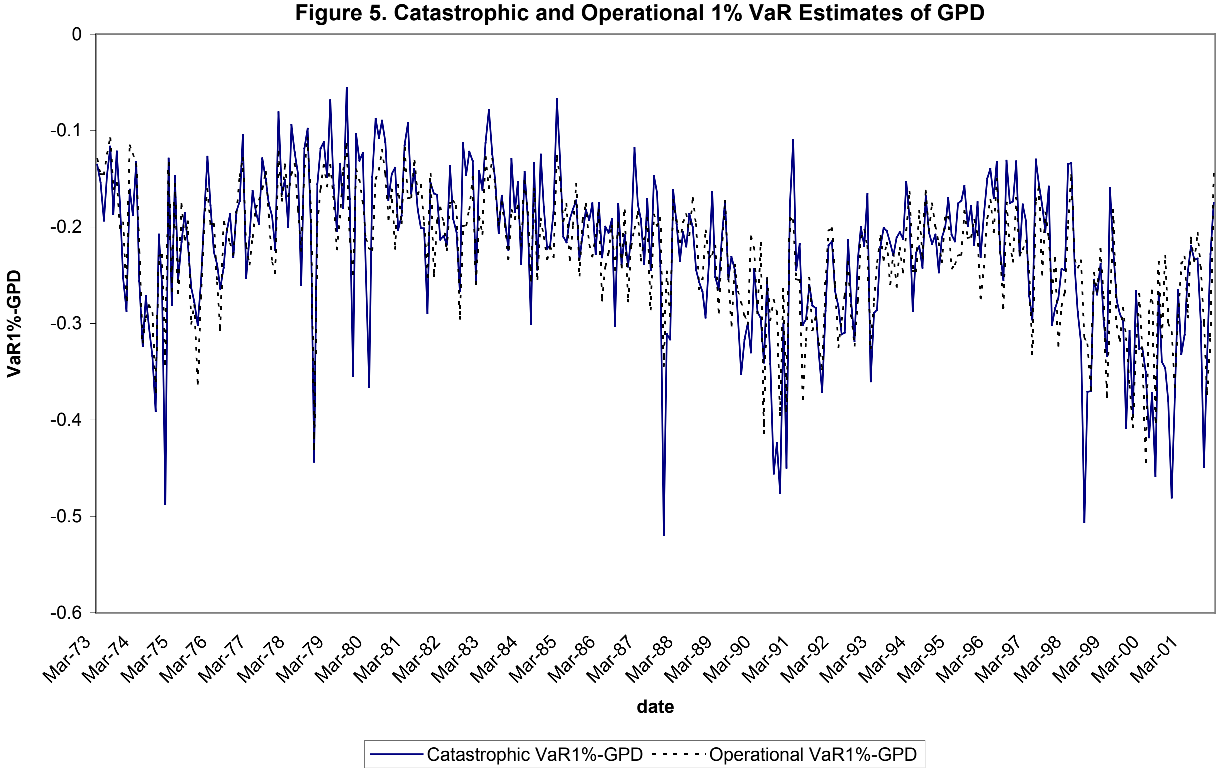

Figure 6. Catastrophic and Operational 1% VaR Estimates of SGED

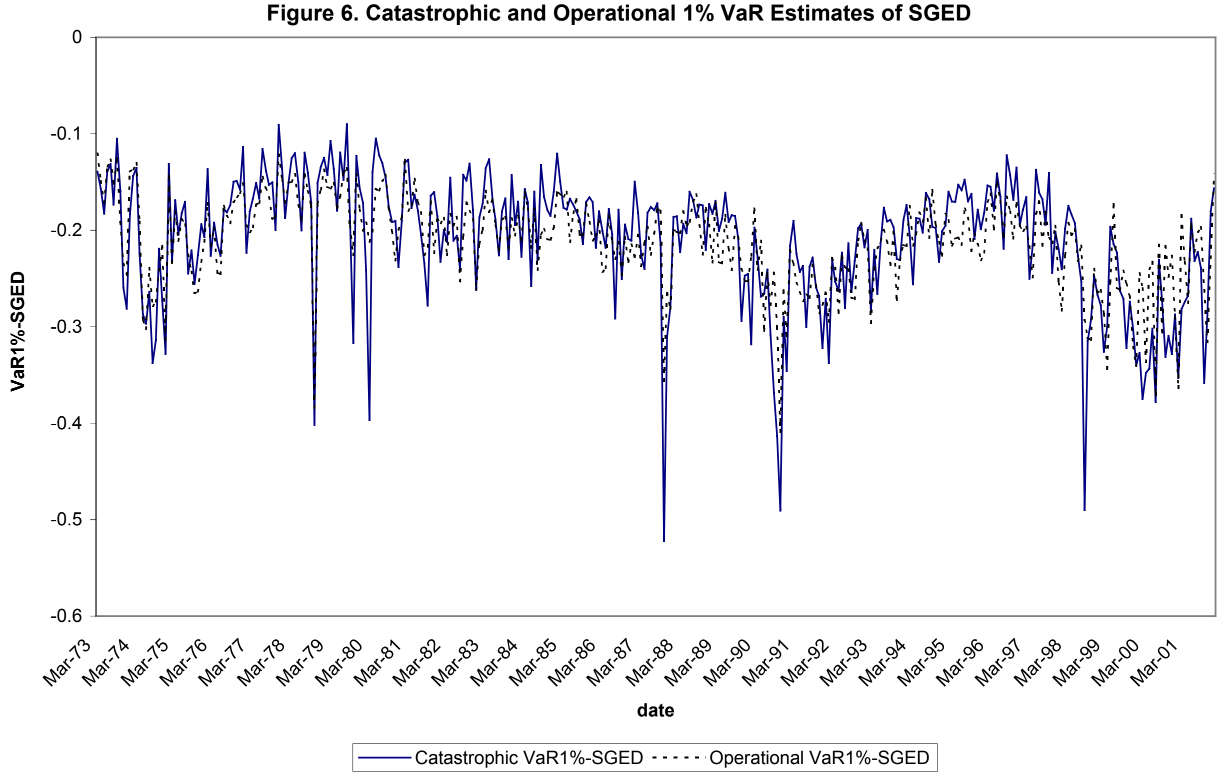

Table 3A. Regression Results from Operational Risk Estimates of GPD

The full model is: *OR-Risk Factor Variable*$_t$ = $\alpha_t + \beta_{1,t}I_{1,t} + \ldots + \beta_{n,,t}I_{n,,t} + \varepsilon_t$ where $I_{1,t} \ldots I_{n,t}$ are the cyclical factor variables listed in Table 1, n=1,…43, t=*January* 1973…*December* 2001. We present only a representative number of the cyclical factor variables in the table. The *OR-Risk Factor Variable*$_t$ takes the value of the location, scale and tail thickness parameters of the GPD estimated using the residual operational risk measure (μ*-ORGPD*, σ*-ORGPD*, and ξ*-ORGPD*, respectively) and the *VaR1%-ORGPD* operational value at risk. Standard errors in parentheses. ***, **, * denote 1%, 5% and 10% levels of significance, respectively.

Variable Name	Location μ-ORGPD	Scale σ-ORGPD	Tail Thickness ξ-ORGPD	Value at Risk VaR1%-ORGPD
Intercept Term	0.002 (0.052)	0.044 (0.044)	-0.553 (0.568)	0.049 (0.084)
Consentiment	-0.0003 (0.0003)	-0.0002 (0.0002)	0.002 (0.003)	0.00007 (0.0005)
IndstryIndex	-0.0006 (0.0006)	0.0004 (0.0005)	0.005 (0.006)	-0.003*** (0.0009)
SPINDX	-0.00002 (0.00002)	0.00003 (0.00002)	-0.0003 (0.0003)	-0.00004 (0.00004)
R_3MTB	0.0009 (0.001)	0.0001 (0.001)	-0.023 (0.014)	0.006*** (0.002)
RM1B3S_a_UZ	0.0002 (0.002)	-0.0009 (0.001)	0.010 (0.017)	-0.0005 (0.002)
RMBANK_a_JP	-0.004 (0.002)	0.003 (0.002)	-0.016 (0.026)	-0.012*** (0.004)
RMGBS_a_UK	0.0005 (0.001)	-0.001* (0.001)	0.033** (0.014)	0.0002 (0.002)
DUM_DIDMCA	-0.004 (0.007)	-0.008 (0.006)	-0.013 (0.082)	0.008 (0.012)
DUM_FDICIA	-0.002 (0.013)	0.0008 (0.011)	0.050 (0.147)	-0.002 (0.022)
DUM_Basel	0.013 (0.013)	-0.017 (0.011)	0.116 (0.140)	0.042** (0.021)
DUM_Interstate	0.016 (0.011)	-0.008 (0.009)	-0.004 (0.122)	0.034* (0.018)
DUM_GLBA	0.011 (0.011)	-0.007 (0.009)	0.101 (0.116)	0.015 (0.017)
DUM_NBER	-0.017** (0.008)	0.003 (0.006)	-0.065 (0.083)	-0.006 (0.012)
Adj. R-square	5.99%	4.54%	4.87 %	28.49%
# observations	342	342	342	342

Table 3B. Regression Results from Operational Risk Estimates of SGED

The full model is: *OR-Risk Factor Variable*$_t$ = $\alpha_t + \beta_{1,t}I_{1,t} + \ldots + \beta_{n,,t}I_{n,,t} + \varepsilon_t$ where $I_{1,t} \ldots I_{n,t}$ are the cyclical factor variables listed in Table 1, n=1,…43, t=*January* 1973…*December* 2001. We present only a representative number of the cyclical factor variables in the table. The *OR-Risk Factor Variable*$_t$ takes the value of the mean, standard deviation, kurtosis and skewness parameters of the SGED estimated using the residual operational risk measure (μ-*ORSGED*, σ-*ORSGED*, ξ-*ORSGED*, and λ-*ORSGED* respectively) and the *VaR1%-ORSGED* catastrophic value at risk. Standard errors in parentheses. ***, **, * denote 1%, 5% and 10% levels of significance, respectively.

Variable Name	Mean μ-*SGED*	Std. Dev. σ-*SGED*	Kurtosis ξ-SGED	Skewness λ-*SGED*	Value at Risk *VaR1%-SGED*
Intercept Term	0.072 (0.048)	0.080*** (0.021)	1.630*** (0.342)	0.828*** (0.218)	-0.073 (0.062)
Consentiment	-0.0006** (0.0003)	-0.0004*** (0.0001)	0.002 (0.002)	-0.003** (0.001)	0.0003 (0.0003)
IndstryIndex	-0.0004 (0.0005)	0.0003 (0.0002)	-0.009** (0.004)	-0.007*** (0.002)	-0.001** (0.0007)
SPINDX	0.00002 (0.00002)	0.00004*** (0.00001)	0.0002 (0.0002)	0.0003*** (0.0001)	-0.00007** (0.00003)
R_3MTB	-0.001 (0.001)	-0.003*** (0.0006)	0.036*** (0.009)	-0.011* (0.006)	0.004*** (0.002)
RM1B3S_a_UZ	0.0004 (0.001)	0.0006 (0.0006)	-0.014 (0.010)	0.009 (0.006)	-0.0005 (0.002)
RMBANK_a_JP	-0.0003 (0.002)	0.002** (0.001)	0.038** (0.015)	-0.034*** (0.010)	-0.008*** (0.003)
RMGBS_a_UK	0.0003 (0.001)	0.0004 (0.0005)	-0.025*** (0.008)	0.010* (0.005)	0.0005 (0.002)
DUM_DIDMCA	0.012* (0.007)	0.009*** (0.003)	0.077 (0.050)	0.059* (0.032	-0.008 (0.009)
DUM_FDICIA	-0.005 (0.012)	-0.002 (0.006)	0.011 (0.089)	-0.061 (0.057)	0.001 (0.016)
DUM_Basel	0.002 (0.012)	-0.012** (0.005)	-0.0008 (0.084)	0.053 (0.054)	0.031** (0.015)
DUM_Interstate	0.006 (0.010)	-0.009** (0.006)	0.033 (0.073)	0.027 (0.047)	0.031** (0.013)
DUM_GLBA	0.014 (0.010)	-0.005 (0.004)	0.038 (0.070)	-0.037 (0.045)	0.021* (0.013)
DUM_NBER	-0.018** (0.007)	-0.004 (0.003)	0.095* (0.050)	-0.044 (0.032)	-0.011 (0.009)
Adj. R-square	0.01%	42.13%	31.11%	2.89 %	29.95%
# observations	342	342	342	342	342